MOREFIELD, GARY BRANT, Ph.D. Empirical Essays in Health and Human Capital. (2011)
Directed by Dr. David Ribar. 141 pp.

This dissertation studies two dynamic processes, the production of human capital and evolution of health. The first essay uses data on parents and their children in the longitudinal Panel Study of Income Dynamics and PSID-Child Development Supplement to estimate the effect negative changes in parental health on the children's development of cognitive and non-cognitive skills. The analysis suggests that the onset of a parental health event, on average, does not affect children's cognitive measures and has small negative effects on the level of children's noncognitive skills. However, small average effects mask heterogeneous effects across: the sex of the parent, sex of the child, and the type of health condition. Parental health events are found to significantly impair noncognitive skill development when a father is afflicted with a health event, affect sons more negatively than daughters, and are worse for certain—vascular or cancerous—conditions. Further exploration shows that effects of parental health events on skill development are related to changes in the hypothesized mechanism, changes in skill investments. Specifically, when parental health events are estimated to create the poorest behavior outcomes, large reductions in one measure of skill investment, time that parents participate in activities with children, is also commonly found.

The second essay (joint with David Ribar and Christopher Ruhm) uses longitudinal data from the 1984 through 2007 waves of the Panel Study of Income Dynamics to examine how occupational status is related to the health transitions of 30 to 59 year-old U.S. males. A recent history of blue-collar employment predicts a substantial increase in the probability of transitioning from very good into bad self-assessed health, relative to white-collar employment, but with no evidence of occupational differences in movements from bad to very good health. These findings are robust to a series of sensitivity analyses. The results suggest that blue-collar

workers "wear out" faster with age because they are more likely, than their white-collar counterparts, to experience negative health shocks. This partly reflects differences in the physical demands of blue-collar and white-collar jobs.

The third essay (joint with Jeremy Bray) uses the framework of Bray (2005) to develop a theoretical and accompanying empirical model examining how the productivities of the human capital inputs work and school are affected if individuals work while enrolled in school.[1] Using data from the National Longitudinal Survey of Youth 1997, we model the dynamic processes of work and school input decisions jointly with the effects of these decisions on future wages to discern whether work and school are contemporaneous complements or substitutes in the production of human capital. Endogeneity is corrected through the use of the Discrete Factor Method. The model shows that, on average, work and school are indeed complementary in the production of human capital. However, examination of in-school work at differing schooling levels or across different student occupations shows that certain types of work and school are complementary when simultaneously undertaken while others are substitutes in the production of human capital.

[1] This research was conducted with restricted access to Bureau of Labor Statistics (BLS) data. The views expressed here do not necessarily reflect the views of the BLS.

EMPIRICAL ESSAYS IN HEALTH AND HUMAN CAPITAL

by

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A Dissertation Submitted to
the Faculty of The Graduate School at
The University of North Carolina at Greensboro
in Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy

Greensboro
2011

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ACKNOWLEDGEMENTS

I gratefully acknowledge the time, effort, and trust that Chris Ruhm and Dave Ribar have shared with me during in their roles as advisors and mentors. I also thank my committee members Jeremy Bray and Chuck Courtemanche. Your advice and encouragement have significantly improved my research. Brad Schwartz, you revealed the work of applied microeconomics to me, recognized and encouraged my interest, and initiated my career path. I thank Andrea Mühlenweg for recognizing and supporting my research agenda and the ZEW for funding and research support. I thank the staff and, especially, participants of the National Longitudinal Surveys and the Panel Study of Income Dynamics. Without your contributions, my work would not have been possible. Importantly, I thank my family and friends for your unwavering support and appreciation of my efforts during my work. Tango, you were my ever patient companion. Ashley, Wyatt, and Sawyer, as I end this process you provide my hope for the future.

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CHAPTER I

PARENTAL HEALTH EVENTS AND CHILDREN'S SKILL DEVELOPMENT

Introduction

The economics literature has convincingly established that poor adult health is related to lower wages, earnings, labor force participation, and hours worked.[2] An individual's poor health affects not only her behavior but extends to other family members as well. For instance, adults alter their labor supply when a spouse (Parsons, 1977; Berger and Fleisher, 1984; Coile, 2004) or elderly parent suffers from poor health (Ettner, 1995, and others). Altered labor outcomes suggest that poor health changes the home environment by shifting budget constraints, varying time commitments, and, following diminished market productivity, decreasing home productivity. A second, separate growing body of research finds that the home environment is critical in the process of a child's skill development. From maternal employment (Ruhm, 2004, and others) to child abuse (Currie and Widom, 2009, and others), a broad range of differences in a child's home environment has been found to affect a child's current and future skills.[3] Jointly, these strands of literature suggest that poor parental health may significantly affect a child's skill development. In the following, I examine the relationship between the onset of poor parental health and the development of children's cognitive and non-cognitive (behavioral) skills. Specifically, I use the Panel Study of Income Dynamics (PSID) to identify when parents are diagnosed with one of several specific medical conditions that are reported to significantly limit their normal daily activities or a more general health problem that limits the parents' work

[2] See Currie and Madrian (1999) for a review of this extensive literature.
[3] See Heckman (2000), Carneiro and Heckman (2003), and Almond and Currie (2010) for reviews of this literature.

capacities and estimate how the onset of these conditions alter two inputs into their children and the resulting skill levels of their children.

While accurate estimates of the number of parents in poor health are not readily available, a significant number of working-age adults in the U.S.—those most likely to have children in the home—report a disability or common medical conditions. A summary of disability statistics from various sources places the number of adults aged 18-64 with a disability limiting normal or work-related activities between 7.6% and 12.8% (Haveman and Wolfe, 2000). Recent estimates on a younger segment of the population, aged 18-44, note that many Americans suffer from specific health conditions: 8.1% suffer from arthritis; 16.8% suffer from chronic joint symptoms; 4.4% report coronary heart disease, angina pectoris, heart attack, or other heart conditions and disease; 0.6% have experienced a stroke; 0.8% suffer from emphysema; 2.8% have chronic bronchitis; 7.6% have asthma; and 1.7% report cancer (Vital and Health Statistics 2009).

Not only do young to middle-age adults report health problems, they also state that their health limits the activities they can perform. Of individuals in the 18-44 age group, 6% report that one or more basic physical activities, such as walking a quarter mile or climbing 10 steps without resting, is "very difficult or cannot be done at all."[4] The individuals in this age group are also seeking medical attention for their health conditions; 11.3% made 10 or more office visits to a doctor in the previous 12 months.

Human capital in children includes both cognitive and non-cognitive skills. Children's skills have been linked to future participation in crime, teenage pregnancy, drug use, and other deviant activities (Cunha, Heckman, Lochner, and Masterov, 2006), as well as educational attainment, earnings, and other future labor market outcomes (Heckman Stixrud, & Urzua, 2006;

[4] The full list of activities includes (1) walking a quarter mile; (2) climbing up 10 steps without resting; (3) standing for 2 hours; (4) sitting for 2 hours; (5) stooping, bending, or kneeling; (6) reaching overhead; (7) grasping or handling small objects; (8) lifting 10 pounds; and (9) pushing or pulling large objects.

Almond and Currie, 2010). Furthermore, research in skill development has shown that costs of late remediation of low skill investment are exceptionally high compared to early remediation (Heckman, 2000). Given the importance of children's skill development on future outcomes and the high costs of late remediation, it is valuable to identify commonly experienced early life events that alter the development of children's skills.

While some adults suffer from persistent childhood health problems and health transitions up as well as down, I am able to identify the onset of disability and diagnosis of a number of activity-limiting medical conditions over time for a sample of parents in the PSID. I combine health information on parents with supplemental household and child achievement data from the PSID-Child Development Supplement (CDS) and examine how measures of children's skills are affected after the onset of a parent's negative health event. The results are consistent with several stylized facts in the previous literature. First, there is heterogeneity in the effects on sons and daughters after a parental health event and heterogeneity in effects for maternal and paternal health events. Second, examining a sample of children affected during late childhood, I find that this is a sensitive period for changes in the household on noncognitive skills but not effects on a cognitive measure. Furthermore, there is evidence that children's noncognitive (behavioral) skills are related to skill investment, as measured by the amount of time parents spend participating in activities with children.

Conceptual Issues

The seminal work of Becker (1981) states that households optimize time- and goods-intensive inputs, given budget constraints, to produce household commodities. One household commodity is the human capital of children. For young children, parents decide when and how to invest in their child's development. Perhaps parents decide to read with their child and promote the development of cognitive abilities. Alternatively, parents may emphasize an emotionally secure environment and social development. Of course these investments are neither mutually exclusive nor exhaustive; parents, most often, will wish to provide all necessary inputs to help their children develop to the highest potential.

When a parent suffers from a negative health change, poor health alters constraints and, therefore, optimal behaviors of the parent. For example, a less healthy adult may be less productive in the labor market and receive reduced wages (Currie and Madrian, 1999), spend family wealth (Wu, 2003) and reduce non-labor income, or limit the number of hours she is capable of working. Poor parental health is therefore suggested to reduce a family's monetary budget constraint and, as normal goods, goods investments in child development. However, behavior changes are not limited to the labor market or goods investments into children's skills. Poor parental health can limit the amount or productivity of time that parents spend with their children (Ruhm, 2004), therefore diminishing time investments in children's development. These hypothesized changes negatively affect the level of time and goods investments in children.[5] The production of skills is a cumulative process. Skills build over time; therefore, a drop in skill investment in any one period will lessen the future levels of skills in all future periods without sufficient remediation. Remediation would come in the form of increased investments in future periods. However, remediation is often difficult and inefficient in skill production. Investments across periods of development are complementary rather than perfect substitutes. Therefore, a

[5] The effect of poor parental health on children's outcomes is not definitively negative or significant. For instance, if the potential market time of a sick parent is reduced, the parent may be able to spend more time with children, contributing positively to skill development through additional, albeit smaller, marginal benefits of additional parent-child time. However, a thorough theoretical model is beyond the scope of this paper. Acknowledging this limit, this paper aims to provide a first attempt at measuring the treatment effect of negative parental health changes on children's skills and investigates if parental health changes are associated with changes in broad measures of the home environment and parent-child time.

reduction in one period of investment will not be remediated by an equal increase in investment in the following period.

Skills also have sensitive periods of development. A sensitive period for a skill is one in which investments are more productive relative to investments in other periods. For instance, Cunha and Heckman (2008) find that cognitive skills are more sensitive to investments at earlier rather than later ages in childhood. Alternatively, the authors find that noncognitive skills are more sensitive to investment changes at later stages of childhood. Diminished skill investment in a sensitive developmental period may be particularly difficult to remediate.

Furthermore, skills themselves are inputs in the production of later skills. Skills are "self-producing." Self-productivity is the notion that a child's stock of skills augments future skill levels. More specifically, lagged skill levels are inputs into the production process of new skill levels. Therefore, a decline in skill development in one period lessens the stock of skills that is productive in future periods. Not only are skills self-producing, but higher skill levels increase the productivity of current and future investments (dynamic complementarity).

The cumulative nature of skill development, sensitive periods, self-productivity, and dynamic complementarity are characteristics of skill development that explain why early life events are so important in future outcomes and why late remediation or attempts to bolster skills in adults is costly compared to early life investments. A number of empirical studies note that a broad range of early life events affect short- and long-term skills measures.

Previous Literature

The relationship between parental health and children's cognitive and behavioral development has been largely ignored in the economics literature, despite the evidence of high returns of early-life skill investment in forming future levels of human capital.[6] However, previous research suggests a significant relationship between the two.

Two studies, Choi (2008) and Haveman and Wolfe (1994), focus on broad measures of poor parental health and their effects on children's outcomes. Choi examines the effect of self-reported poor parental health on labor market outcomes of Russian children. The results indicate that poor paternal health reduces his daughter's future probability of working and attending higher education. Neither maternal nor paternal poor health significantly altered the outcomes for sons. However, the children studied in Choi's analysis were 13-29 years old at the original observation. Although these children were initially living at home, the sample of older children in Choi's analysis is likely to identify changes in labor force participation similar to those in studies of the effects of poor health of elderly parents on the labor supply of adult children. Indeed, Choi's results reflect those found in the research on poor elderly parental health on adult children's labor supply, that daughters assume most of the parental care and reduce their labor force participation to accommodate parental needs (Stone, Cafferata, and Sangl, 1987, and others).

Haveman and Wolfe (1994) study children in the multi-generational PSID who lived with a "head of household" that reports a work-limiting disability. The estimates of their work suggest that living with a disabled head of household for 10 years during childhood lowers the probability of high school graduation by 11.8 percentage points and leads to three fewer years of completed schooling. The focus of the authors' work, however, is how a broad array of investment measures, only one of which is living with a disabled head of household, are related to child outcomes. While this work is seminal in highlighting the importance of child investments on future outcomes, the use of a broad array of investment measures as dependent variables limits

[6] See Heckman (2000), Carneiro and Heckman (2003), and Almond and Currie (2010) for summaries of recent research.

the interpretation of the effect of a disabled parent on future outcomes. For example, by including the number of years the head of household was disabled and the number of years that the family was in poverty as covariates, the authors estimate the effects of the former independent of the effects of the latter. This model is useful in controlling for effects of poverty on wages that are correlated with but not caused by disability status of the household head. However, if disability status causes the family to be in poverty, and both variables are included in the model, then this effect is excluded from the estimated effect of parental disability on child outcomes. As a result, Haveman and Wolfe show that parental health is related to child outcomes but may over control for the potential pathways for its effects on outcomes.

A number of previous studies have examined the impact of parental psychiatric illness, commonly depression and substance abuse, on children's outcomes. The results consistently show that children of depressed mothers demonstrate worse behavior during childhood without significant effects on measures of cognitive skills (Kim-Cohen et al., 2005; Frank and Meara, 2009). Two studies do, however, find that maternal depression negatively affects children's cognitive skill development. Examining the effects of maternal depression on very young children, aged 1 (Cogill et al., 1986) and 2-4 years (Petterson and Albers, 2001), maternal depression has been found to significantly reduce early measures of the children's cognitive outcomes. Looking at future outcomes of children, Farahati et al. (2003) find that parental psychiatric illness is associated with a significantly lower probability of high school graduation, suggesting the effects remain the long-term.

This study improves on the previous literature in a number of ways. This is the first study to examine two broad measures of general health problems in a sample of U.S. families and how these alternative measures compare in their estimated effects on children's skill levels. Furthermore, this is the first study, in the economics literature, of the effects of parental health and children's outcomes that also examines the effects of potential intermediate mechanisms for how parental health events may alter children's skills—parent-child time and alteration of a home environment index. The results show that these contributions are relevant to studies of parental health and children's skill development. The onsets of two alternative definitions of broad parental health conditions provide similar average effects on skill development. Furthermore, by examining conditions, as well as inputs into skill production, I show that heterogeneity in effects of parental health conditions on children's skills across disaggregated medical conditions, effects for sons versus daughters, and maternal versus paternal health events are related to how one proxy measure of total skill investments is affected by the parental health condition.

The previous theoretical and empirical literature indicates three stylized facts that are particularly relevant for this study. First, there are sensitive periods for development of differing skill types. Cunha and Heckman (2008) directly test for periods when cognitive and behavioral measures are more sensitive to investments by testing and rejecting the hypothesis that the parameters associated with skill investments are invariant over differing age ranges in childhood. The estimates of Cunha and Heckman assert that cognitive skills are more sensitive to changes in investments during the earliest ages in their sample, ages 6 and 7, and noncognitive skills are more sensitive to changes in investments at later ages. The most sensitive period for noncognitive skills is transitioning between ages 8 and 11 years old. While not directly testing for sensitive periods, other empirical literature described above supports these findings. Only studies examining very young children (Cogill et al., 1986; Petterson and Albers, 2001) found effects of the variables of interest on cognitive outcome measures during childhood. However, many of the studies, examining children older than 5, have found that behavior outcomes for children are malleable to depression, changes in family structure, and alcohol abuse by parents.

A second stylized fact is that shocks to the home environment may affect sons and daughters differently. In addition to the literature, Choi (2008), showing differing effects on sons and daughters, above, empirical literature outside of this review has often found differing outcomes by sex. Examples of son and daughter differences in skill effects are found from low birth weight (Currie and Hyson, 1999), prenatal alcohol exposure (Nilsson, 2008), parental problem drinking (Balsa, 2008), foster care (Doyle, 2008), child abuse (Currie and Widom, 2009), and father's absence (Mott, 1994; Lang and Zagorsky, 2001; and Corak, 2001). Studies that do not report differences by sex of the child often do not report whether they examined differences by sex, making it difficult to determine whether or not there are significant differences in effects. However, there is sufficient evidence to indicate an investigation of heterogeneous effects of parental health events on skill development by sex of the child is warranted.

A third stylized fact, shown by a wide array of research topics, is that familial behavior changes are dependent upon whether or not the wife or husband is the affected spouse. For instance, the work of Choi (2008) found evidence that daughters' labor supply was affected by poor paternal but not maternal health. Futhermore, studies by economists have commonly found that wives[7] and, more specifically, mothers (O'Hara, 2004) increase labor supply when husbands are affected by poor health. Alternatively, effects of wives' health on husbands' labor supply is more mixed. If familial responses to similar types of shocks vary depending upon the sex of the afflicted spouse, then effects of children's attainments may also follow this distinction.
Given the stylized facts, I examine heterogeneity in the effects of parental health events on children's skill development across these distinctions: age of the child at onset, sex of the child, and sex of the afflicted parent.

[7] Bartel and Taubman, 1986; Berger, 1983; Berger and Fleisher, 1984; Charles, 1999.

Estimating the Production Function

The work of Cuhna and Heckman (2007) provides a formal framework for the development of children's skills. For simplicity, suppose skills are categorized as either cognitive, *C*, or noncognitive, *N*. The production of skill θ^k, $k \in \{C, N\}$, is a function of a investment in those skills, I^k, and the skill levels attained by the individual up to the current time period.[8] More specifically,

$$\theta_t^k = f_k(\theta_{t-1}^C, \theta_{t-1}^N, I_t^k), \quad k \in \{C, N\}. \qquad (1)$$

By recursively substituting for the previous period skill level in the production function, the production of the current period's skills can be represented as a function of all previous inputs and the child's initial skill level, or "innate" ability ($\theta_0{}^C$ and $\theta_0{}^N$),

$$\theta_t^k = f_k(\theta_0^C, \theta_0^N, I_t^k, I_{t-1}^k, ..., I_0^k). \qquad (2)$$

The production function represented by (2) shows that the development of a child's skill level depends on *all* previous investments. As a result, a change or shock to investment in any period can alter the child's level of skill in future periods, ceteris paribus, emphasizing the cumulative nature of skill development. In this framework, parental health events will alter the investments into the production of a child's skills and, ultimately, the stock of skills.

Considering that parental health can affect family investments, family investments are considered a function of parental health, h^p, and a vector of other parent and child characteristics, $I_t^k(h_t^p, X_t)$. Parental health may be thought of as current health and the health history of the parent. Health history is a determinant of investments if the parent wishes to compensate for poor

[8] This vector of investments can easily be thought of as time-intensive commodities, X_L, and goods intensive commodities, X_G. For simplicity, I simply note investments, *I*, in skill *k*.

health in previous periods with greater levels of investment in future periods. Production function (2) is now represented as

$$\theta_{t+1}^{k} = f_k(\theta_0^C, \theta_0^N, I_t^k(h_t^p, X_t), I_{t-1}^k(h_{t-1}^p, X_{t-1}), \ldots, I_0^k(h_0^p, X_0)). \qquad (3)$$

The technology represented in (4) shows that parental health will alter the level of a child's cognitive or noncognitive skill if it alters the family investments in the outcome.

Assume a linear relationship for equation (1) such that

$$\theta_t^k = \beta_{1,k}\theta_{t-1}^k + \beta_{2,k}\theta_{t-1}^j + \beta_{3,k}I_t(h_t^p, X_t). \qquad (4)$$

By recursively substituting for skill *k* and rearranging terms, equation (4) yields:

$$\theta_t^k = \beta_{1,k}^t\theta_0^k + \beta_{2,k}\sum_{i=1}^{t}\beta_{1,k}^{i-1}\theta_{t-i}^j + \beta_{3,k}\sum_{i=1}^{t}\beta_{1,k}^{i-1}I_{t-i}(h_{t-i}^p, X_{t-i}). \quad (5)$$

Equation (5) shows that under the assumptions of a linear production technology and geometric rate of decay for the effects lagged skills and investments equal to $\beta_{1,k}^{t-1}$ that equation (4) is a directly estimable linear equation capturing the cumulative nature of skill development with lagged measures of skills and current investments. However, these two assumptions must be addressed.

Linear production technology imposes upon the specification that early and late investments are perfect substitutes. Because the investment change of interest is alterations due to parental health events, I run models that include indicator variables over five-year age ranges to examine if effects are uniform over time. This approach, while not correcting for imposing perfect substitution across investments, does allow for the effect of changes in investment to vary depending on the age of the child.

Assuming that the effects of investments geometrically decay at the rate of $\beta_{1,k}{}^{t\text{-}1}$ will necessarily affect the coefficient of interest $\beta_{3,k}$. Suppose that investments do not decay at the rate $\beta_{1,k}{}^{t\text{-}1}$, if we force this form upon the estimating equation then the estimate of $\beta_{3,k}$ will necessarily be biased to offset the deviation from this assumed rate of decay. More specifically, when we state that the effects of investments evolve as $\sum_{i=1}^{t} \beta_{1,k}^{i-1} I_{t-i}(h_{t-i}^{p}, X_{t-i})$ then when we estimate this form as $\beta_{3,k} \sum_{i=1}^{t} \beta_{1,k}^{i-1} I_{t-i}(h_{t-i}^{p}, X_{t-i})$, β_3 will change to accommodate deviations from the $\beta_{1,k}^{i-1}$ assumption.

To help correct for this potential misspecification, Todd and Wolpin (2007) suggest including lags of the investment variables. The authors describe this as the "value-added plus" model. The model will then have lags of the investment measures such that

$$\theta_t^k = \beta_{1,k}\theta_{t-1}^k + \beta_{2,k}\theta_{t-1}^j + \beta_{3,k} I_t\left(h_t^p, X_t\right) + \beta_{4,k} I_{t-1}\left(h_{t-1}^p, X_{t-1}\right) + \cdots + \beta_{t+2,k} I_0\left(h_0^p, X_0\right). \quad (6)$$

Recursively substituting for skill k and rearranging terms, equation (6) yields:

$$\theta_t^k = \beta_{1,k}^t \theta_0^k + \beta_{2,k} \sum_{i=1}^{t} \beta_{1,k}^{i-1} \theta_{t-i}^j + \beta_{3,k} I_t\left(h_t^p, X_t\right) + \left(\beta_{1,k}\beta_{3,k} + \beta_{4,k}\right) I_{t-1}\left(h_{t-1}^p, X_{t-1}\right) + \cdots$$
$$+ \left(\beta_{1,k}^{t-1}\beta_{3,k} + \beta_{t+2,k}\right) I_0\left(h_0^p, X_0\right). \quad (7)$$

We can see from equation (7) that the value-added plus model allows for scalar adjustments to the decaying effect of previous investments, $\beta_{4,k}$ through $\beta_{t+2,k}$. These scalar adjustments relax the assumption. However, the coefficients $\beta_{4,k}$ through $\beta_{t+2,k}$ do not measure the effect of lagged investments. They measure differences in the rate of decay from the forced specification. Therefore, these coefficients are not interpretable as effects.

The "value-added plus" model has been estimated on children's cognitive skill development and was shown to perform better than alternative specifications, including a simple value-added model and a child fixed-effects model, on out-of-sample prediction (Todd and Wolpin, 2007). Equation (6), therefore, is the preferred empirical specification.

Unobserved Heterogeneity

Suppose that instead of the production function presented in (4), the true model of children's skill development is

$$\theta_t^k = \beta_0 + \beta_1\theta_{t-1}^k + \beta_2\theta_{t-1}^j + \beta_3 I_t + \beta_4 v_{t,i} \qquad (8)$$

where v_i is unobserved heterogeneity for child *i*.

Thus,

$$\theta_1^k = \beta_0 + \beta_1\theta_0^k + \beta_2\theta_0^j + \beta_3 I_1 + \beta_4 \upsilon_{1,i}$$

and

$$\begin{aligned}\theta_2^k &= \beta_0 + \beta_1\theta_1^k + \beta_2\theta_1^j + \beta_3 I_2 + \beta_4\upsilon_i \\ &= \beta_0 + \beta_1\beta_0 + \beta_1^2\theta_0^k + \beta_1\beta_2\theta_0^j + \beta_2\theta_1^j + \beta_1\beta_3 I_1 + \beta_3 I_2 + \beta_1\beta_4\upsilon_{1,i} + \beta_4\upsilon_{2,i}\end{aligned}.$$

At the end of period 2, the true level of a child's skill is

$$\theta_2^k = \beta_0 + \beta_1\beta_0 + \beta_1^2\theta_0^k + \beta_1\beta_2\theta_0^j + \beta_2\theta_1^j + \beta_1\beta_3 I_1 + \beta_3 I_2 + \beta_1\beta_4\upsilon_{1,i} + \beta_4\upsilon_{2,i}. \qquad (9)$$

If I estimate (4) in lieu of (8), the hypothetically true model, I will estimate

$$\hat{\theta}_t^k = b_0 + b_1\theta_{t-1}^k + b_2\theta_{t-1}^j + b_3 I_t + e.$$

The child's estimated level of skill after two periods is

$$\hat{\theta}_2^k = b_0 + b_1 b_0 + b_1^2 \theta_0^k + b_1 b_2 \theta_0^j + b_2 \theta_1^j + b_1 b_3 I_1 + b_3 I_2 + b_1 b_4 \upsilon_{1,i} + e \,. \quad (10)$$

In order for (10) to provide an unbiased estimate of (9), the expectation of error term must equal zero, E[$e|\boldsymbol{\theta}_{t-1},I,\mathbf{b}$] = 0. However, equating the right hand sides of (9) and (10) it can be seen that E[$e|\boldsymbol{\theta}_{t-1},I,\mathbf{b}$] = $\beta_4 v_i \neq 0$. The value-added specification does, however, capture the lagged effect of unobserved heterogeneity. Therefore, the value-added model controls for lagged unobserved heterogeneity but is still affected by current effects of unobserved heterogeneity.

Data

To investigate the impact of health events on human capital development of children, I use the PSID and the CDS. The PSID began surveying "heads" and "wives" of a nationally representative sample of 4,800 families in 1968, focusing on the economic and income behavior of the family.[9] The PSID has continued to follow these families over time and includes information on the children of the original cohort, and subsequent cohorts, after they have started independent households. The focus on "heads" and "wives" of families in the PSID limited the available information on children until 1997, when the PSID began collecting the CDS.
The CDS began interviewing a nationally representative sample of 3,563 children, aged 0-12, from 2,394 families in 1997. The CDS gathers extensive childhood information on "health, psychological well-being, social relationships, cognitive development, achievement motivation, and education, as well as a number of measures of the family, neighborhood, and school environments" (Mainieri, 2006, p.1). Accompanying this information are time diaries for

[9] Family "heads" are defined as the primary financial contributor to a PSID family, but defaults to the male partner of a female primary financial contributor if the male is a husband or has cohabited with the "wife" for at least a year.

children aged 3 and older. The CDS conducted a second wave of interviews in 2002, following the same children. Once the CDS children turn 18 years of age and complete high school, they are followed by the PSID Transition into Adulthood (TA) supplement until they begin an independent household and are deemed “heads” or “wives” of PSID families and are followed by the PSID’s primary interviews.

For the purpose of the current analysis, parents are defined as the mother or father figures present in the household, given that one figure is the mother or father (biological or adoptive). Therefore, I have defined parents as the parental figures present in the household at each survey. An example of where this definition matters is if a father moves out of the household and the mother remarries; the stepfather is now defined as the “father.”

Health Events

I use self-reported health information in the PSID to identify two types of parental health events. The first health event is the date of diagnosis for several specific conditions that are reported to limit the parent’s normal daily activities “somewhat” or “a lot.” The conditions include stroke, heart attack, heart disease, hypertension, asthma, lung disease, diabetes, arthritis, memory loss, learning disorders, cancer, and psychiatric problems. The second type of health event is the report of a non-specified physical condition that limits the type of work a person can perform to “can do nothing” or the amount of work by “a lot.” To identify entering into a work-limiting physical condition, I restrict this group to parents who report a work-limiting condition but have not reported a work-limitation in the previous four years.

I have chosen these measures of health events, over the available alternatives, for several reasons. First, given the above discussion of how parental health events may alter the investments in children's skills—by altering constraints and, therefore, inputs into children's skills—I have identified two definitions that provide self-reported indications that the health changes altered the behavior of the parent, limiting work or daily activities. Although these behaviors are not necessarily parenting behavior, it is a straightforward assumption that inputs into children are more likely to be altered if other behaviors change. Second, the measures of specific health conditions may provide greater comparability across respondents, as the conditions are better defined, than more subjective measures such as self-reported health status. Third, the measures of specific conditions, but not work limitations, may be less likely to be used as justification for other behaviors, such as less-intensive work hours, than general health status indicators. Fourth, the measures of specific conditions ask retrospective information in addition to contemporary information leading to a lower probability of missing periods where individuals experience shocks and then recover.

There are, however, several potential problems with using self-reports of specific health conditions as measures of health events. The retrospective nature of the questions demands a strong memory of the respondent. For instance, Smith (2007) finds that dates reported for the onset of conditions in the PSID are centered on 5, 10, 15, 20 years ago. However, this clustering is less common for more serious (cancer, stroke, and heart disease) or recent health events, which lessens the concerns for the current study as I focus on activity-limiting behaviors in the recent past.

Two additional concerns are due to the wording of the PSID question, "Has a doctor ever told you that you have or had any of the following—?" This word choice does not define what a doctor is, nor does it ask if a doctor has *diagnosed* the condition. These potential problems with the wording are a potential cause for concern regarding false positives (reporting of a condition that does not have a corresponding condition) due to self-diagnosis or preliminary diagnosis by doctors. Baker, Stabile and Deri (2004) compare self-reported incidence of conditions with medical records and find a considerable proportion of both false positives and false negatives but that false positives decrease with the intensity of the condition. Again, since I am attempting to identify more severe conditions that will alter the behavior of individuals, this tempers these specific concerns. Baker et al. also show that false positives occur less frequently for individuals younger than 40 years old, which well describes the sample of CDS parents.

Outcomes

The primary outcomes of interest measure the children's cognitive skill level and problem behavior. The measure of cognitive skills is the Revised Woodcock-Johnson (WJ-R) applied problem achievement test. The WJ-R applied problem test evaluates a child's ability to solve practical mathematical questions. The WJ-R test measures quantitative knowledge, one factor related with human intelligence (Woodcock, 1998). WJ-R tests are widely used standardized assessments of educational achievement shown to be highly reliable.

The measure of problem behavior comes from the Behavior Problems Index (BPI) developed by Peterson and Zill (1986). The BPI is a summation score of 28 questions posed to the primary caregiver of the child and contains subsets of questions identifying internalizing and externalizing problem behaviors. The BPI has been shown to identify three serious factors in children's problem behavior: depressed/withdrawn, antisocial, and impulsive hyperactive behavior. This is also the base measure of noncognitive skills used by Cunha and Heckman (2008) and has been used extensively in studies of child and adolescent development.

The scores for the WJ-R applied problem test are age-standardized. Alternative measures of the available WJ-R tests are the raw and percentile ranking scores. Although the BPI score is not age standardized, all regression equations below flexibly account for the age of the child using indicator variables for three-month age ranges. I have transformed the WJ-R and BPI scores to have a mean of zero and standard deviation of one to increase the ease of interpreting the results.[10] There is not a loss of information by transforming the scores, since this monotonic transformation preserves the ranks and the measures do not have natural interpretations.[11]

Measures of Inputs

The first measure of parental inputs into children's skills is an index measuring the cognitive and emotional support of the child's home, the Home Observation and Measurement of the Environment-Short Form (HOME-SF). The HOME-SF is a series of questions derived from the Caldwell and Bradley HOME inventory (Caldwell and Bradley, 1984) specific to the child's age (0-2, 3-5, 6-9, and 10+) designed to systematically evaluate a child's home learning environment. The raw score of the HOME-SF is the summation responses that are deemed beneficial to the child. The CDS-provided HOME-SF score in 2002 omitted nine questions originally included in the 1997 CDS interview, due to low response rates.[12] I recoded this variable to include the missing questions, when available, so that the HOME-SF score reflects the CDS-provided 1997 score and that used in the Children of the National Longitudinal Survey of Youth. Furthermore, I include the matching lagged value of the HOME-SF score as a control variable. Unfortunately, I am not able to re-construct the 2002 HOME-SF score for all

[10] The BPI scores were also reversed so that a lower score indicates worse behavior.
[11] I have also examined models where the dependent variables are raw scores of the WJ-R and BPI outcomes. The qualitative results are similar between the standardized and raw score models.
[12] Certain questions in the HOME-SF are simple observations by the interviewer. Families deemed "out of range" by the PSID were interviewed by telephone or mail methods only (CDS-II User Guide, p. 31).

individuals and the resulting sample size is limited to 1,218 of 1,356. The possible range for the HOME-SF raw score is 0 to 24. The HOME-SF scores in the sample are distributed with a mean of 17.7 and a standard deviation of 3.

The second measure of home inputs examined is parental time involvement with children. The CDS attempts to collect two 24-hour time diaries, one week day and one weekend day, for children. From this information I construct a variable representing the total amount of time that a parent is participating in an activity with the child over both diary days. The variables were again recoded to represent the number of hours a parent participated in activities over a week.

Descriptive Statistics

The dataset used in the current analysis was assembled by matching the primary family PSID files and individual files for "heads" and "wives" over the life of the CDS children. Of the original CDS cohort, I drop observations who do not have WJ-R applied problem and BPI scores from both the 1997 and 2002 interviews (n = 2124) and those without at least one parent (biological, step, or adoptive) as a PSID "head" or "wife" or are missing interviews at the 1997 and 2003 interview dates (n = 116). The first restriction provides information on children at two points in time. The second restriction allows me to identify parental characteristics of the children in the main PSID family files before and after the CDS interviews. Finally, I drop observations who are missing information in the list of covariates described below in Section 5 (n = 16). The restrictions limit the sample to 1,378 children aged 8-18 at the 2002 interview.

The PSID sample includes a significant number of children with at least one parent who experienced a specific health condition and reported that the condition limited the parent's normal daily activities "somewhat" or "a lot" during the 1999, 2001, or 2003 PSID interviews. The top panel of Table 1.1 provides the number of children with at least one parent who experienced each of the specific health conditions and the total number of children whose parent(s) experienced at least one activity-limiting health condition. Of the 1,378 children in the sample, 206 (15%) children had a parent who experienced the onset of an activity-limiting health condition between the 1997 and 2002 CDS waves; 229 (17%) children had a parent experience one or more activity limiting health conditions prior to the 1997 interview; and 1,028 children had parents without an activity-limiting health condition prior to the 2002 CDS survey. The table also reveals a significant number of comorbidities for parents. For example, of the 206 children with parents who experienced at least one specific condition, the total number of diagnosed conditions during this time was 279. Not shown, 85 children had a parent who experienced a specific condition prior to and an additional condition after the 1997 interview.

The second panel of Table 1.1 shows the number of children with a parent who reported suffering from one or more of the listed conditions and the condition is reported to limit their normal daily activities "just a little" or "not at all." Most of the children had a parent experience at least one of the listed conditions before the second CDS interview in 2002. A number of the conditions are common among adults and may not immediately threaten to significantly limit the parent's daily activities (i.e. high blood pressure or asthma). Roughly 38% of the children (n = 530) had no parent in the household report one of the listed conditions prior to the 2002 CDS interview.

The bottom panel of Table 1.1 shows the number of children with a parent who reported a work-limiting physical or nervous condition. The new onset work limitation (between 1997 and 2002) is defined by a parent who reported a limitation between the 1997 and 2003 interviews and did not report a work limitation during the four prior interviews (1994, 1995, 1996, 1997). The number of children whose parent(s) reported a new work limitation is 121, while the number of children with a parent who reported a work limitation prior to the 1997-2002 period is 204.

Table 1.1
Number of Children with at leas one Parent Experiencing a Health Shock by Type and Date of Onset

	1997 < Onset < 2002				Onset < 1997			
Specific Conditions								
Has a doctor ever told you that you have or had any of the following?								
This condition limits her normal daily activities 'somewhat' or 'a lot'.								
Physical								
Vascular								
Stroke	5				8			
Heart attack	6	70			9	76		
Coronary heart disease, angina, congestive heart failure	19				22			
High blood pressure or hypertension	50				53			
Respiratory								
Chronic lung disease such as bronchitis or emphysema	11	20	181		30	75	193	
Asthma	12				57			
Lifestyle				206				229
Diabetes or high blood sugar	26	110			16	79		
Arthritis or rheumatism	88				68			
Cancer								
Cancer or a malignant tumor, excluding skin cancer	10	10			10	10		
Mental								
Permanent loss of memory or mental ability	12	45	45		14	66	66	
Any emotional, nervous, or psychiatric problems	40				60			
Non-limiting Specific Conditions								
Reports an above condition that limits normal daily activities 'just a little' or 'not at all'.	525				550			
Work Limitations								
Do you have any physical or nervous condition that limits the type of work or the amount of work you can do? The respondent also answered that this condition limits the type of work to 'can do nothing' or the amount of work by 'a lot'.	87				125			
Non-limiting Work Conditions								
The respondent also answered that this condition limits the type of work to 'can do nothing' or the amount of work by 'a lot'.	188				326			

Data reflect health information on 'Heads' and 'Wives' of families for children in the Panel Study of Income Dynamic's Child Development Supplement. Sample size is 1,356 children.

Table 1.2 shows basic, unweighted, demographic characteristics of children in the sample whose parents experienced no health events and children whose parents experienced at least one health event after 1997. The selected demographics describe the children (age, sex, race), the household (two-parent, number of children, mother's age), and characteristics related to the level of investment in children (mother's education level, family income, whether the child was breast fed, if the family has been short of money for food).

Children of parents experiencing the onset of a new specific activity-limiting health condition are approximately 0.5 year older on average, reflecting mothers who are also slightly older on average, are less likely to be male or white, and live in households with two parents and numbers of children at rates roughly the same as the children of parents not experiencing a new activity-limiting condition. There are striking differences between these two groups, however, in the measurement of characteristics related to investment in children. Children of parents with a new activity-limiting health condition are more likely to be in families with a mother who did not graduate from high school (20% vs. 7%), live in families where the income is roughly 20% less ($39,640 vs. $50,387), have recently experienced an occasion where the family was short of money for food (35% vs. 17%), and were less likely to be breast fed as an infant (39% vs. 47%).

Comparing the descriptive measures of families that experience a significant work limitation to those who do not conveys a similar relationship as that seen between families with specific health conditions and those without. Specifically, the families are demographically similar in age of the child and mother and number of parents and children in the household. However, families experiencing a work limitation show more signs related to disadvantage: they are less likely to be white; have less educated mothers; and have a lower level of household income.

The differences in the observed characteristics between families that have and have not experienced the onset of an activity-limiting health condition suggests that there are also unobserved differences between these families that affect the skill development of children.

Table 1.2
Select Descriptive Statistics of CDS Children by Parental Health Shock Status

	Specific Conditions		Work Limitation	
	No Event	New Event	No Event	New Event
Child's age, 1997	7.53	7.97	7.58	8.00
	(0.08)	(0.20)	(0.08)	(0.39)
Male	0.51	0.46	0.51	0.44
	(0.01)	(0.03)	(0.01)	(0.07)
White	0.54	0.46	0.53	0.44
	(0.01)	(0.03)	(0.01)	(0.07)
Two parent family, 1997	0.74	0.71	0.73	0.71
	(0.01)	(0.03)	(0.01)	(0.07)
Number of children in HH, 1997	2.31	2.51	2.34	2.31
	(0.03)	(0.08)	(0.03)	(0.12)
Mother's age, 1997	34.83	35.57	34.97	34.18
	(0.18)	(0.47)	(0.17)	(1.20)
Mother is high school dropout	0.07	0.20	0.09	0.19
	(0.01)	(0.03)	(0.01)	(0.06)
Average family income, 1994-1996	$50,387	$39,640	$49,062	$40,966
	(1509.91)	(2860.75)	(1363.99)	(9490.21)
Child was breast fed	0.47	0.39	0.46	0.42
	(0.01)	(0.03)	(0.01)	(0.07)
Ever short of money for food, 1995-1997	0.17	0.35	0.20	0.19
	(0.01)	(0.03)	(0.01)	(0.06)

Notes:

1. Data drawn from the Panel Study of Income Dynamics Main Family and Child Development Supplement files
2. Specific conditions include stroke, heart attack, heart disease, hypertension, asthma, lung disease, diabetes, arthritis, memory loss, learning disorders, cancer, and psychiatric problems reported to limit the parent’s normal daily activities “somewhat” or “a lot”
3. Work limitations are non-specified physical conditions that limit the type of work a person reports to “can do nothing” or the amount of work by “a lot”
4. New Events include the onset of a specific health condition after the 1997 CDS interview and prior to the 2002 interview. No Event includes children whose parents did not suffer a health event prior to the 1997 CDS interview or between the 1997 and 2002 interviews.
5. Clustered standard errors in parentheses

Furthermore, the differences between the two groups of children suggest that children of families that experience a new limiting condition have unobserved differences related to lower skill investments and worse skill outcomes.

Unobserved heterogeneity is a concern in this study, as it is in most studies. However, two characteristics of this study lessen the concerns about the effects of unobserved heterogeneity. First, the value-added plus model specified in equation (6) controls for unobserved heterogeneity up to the first CDS interview. The effects of possible omitted variables bias are therefore limited to the period between CDS surveys. Second, the PSID and CDS data contain a vast array of information beyond the characteristics in Table 1.2 that I use as controls in the empirical specification. The complete list of covariates is listed in Table 1.4 and discussed below.

Table 1.3 shows the average outcome variables for the children in families experiencing no new parental health events and new parental health events. The baseline measurement scores for both the WJ-R Applied Problem and Behavior Problem Index show that children of parents who experience an activity-limiting specific health condition or significant work limitation between the CDS surveys begin the observation period with lower average WJ-R Applied Problem and BPI scores. The baseline scores of children with a parent who soon experiences a new health limitation, by either definition of a health event, are on average 0.25 standard deviations below the mean of zero for the Applied Problem test. The baseline BPI scores are 0.23 and 0.47 standard deviations below the mean for children of parents with a soon-to-be activity limiting specific health condition and significant work limitation, respectively. The average changes in scores for children of parents with and without health events, however, are not statistically different from zero for either the cognitive or behavioral outcome. Moreover, the average changes in scores are not large in magnitude—less than 0.08 standard deviations for all mean changes. The average changes in scores suggest that children's skills are not significantly affected after a parent experiences the onset of a limiting health experience.

Table 1.3
Outcome Measures of CDS Children by Parental Health Shock Status

	Specific Conditions		**Work Limitation**	
	No Event	**New Event**	**No Event**	**New Event**
WJ-R Applied Problem, 1997	0.045	-0.257	0.009	-0.252
	(0.029)	(0.066)	(0.027)	(0.138)
Behavior Problem Index, 1997	0.041	-0.234	0.017	-0.470
	(0.028)	(0.078)	(0.027)	(0.188)
Δ WJ-R Applied Problem, 1997 to 2002	0.011	-0.062	-0.002	0.043
	(0.027)	(0.062)	(0.025)	(0.124)
Δ BPI, 1997 to 2002	0.012	-0.067	-0.003	0.080
	(0.027)	(0.081)	(0.026)	(0.169)

Notes:

1. Data drawn from the Panel Study of Income Dynamics Main Family and Child Development Supplement files
2. Specific conditions include stroke, heart attack, heart disease, hypertension, asthma, lung disease, diabetes, arthritis, memory loss, learning disorders, cancer, and psychiatric problems reported to limit the parent's normal daily activities "somewhat" or "a lot"
3. Work limitations are non-specified physical conditions that limit the type of work a person reports to "can do nothing" or the amount of work by "a lot"
4. New Events include the onset of a specific health condition after the 1997 CDS interview and prior to the 2002 interview. No Event includes children whose parents did not suffer a health event prior to the 1997 CDS interview or between the 1997 and 2002 interviews.
5. Clustered standard errors in parentheses

Multivariate Results

To discover if and how parental health events are related to the levels of children's cognitive and noncognitive skill levels, I will focus on the value-added plus equation, (6), described above. Equation (6) specifies current skills as a function of lagged levels of skills, investments in the previous period, and lagged measure of investment. The PSID specific counterpart to this equation is:

$$\theta^k_{2002,i} = \beta_0 + \beta_1\theta^k_{1997,i} + \beta_2\theta^j_{1997,i} + \beta_3 Event_{1997-2002,i} + \beta_4 Event_{<1997,i} + \boldsymbol{\delta}\mathbf{X}_{1997,i} + \varepsilon_i, \qquad (11)$$

where θ^k_i is the measure of child *i*'s cognitive or noncognitive skill; θ^j_i is the measure of the alternative skill type; $Event_{1997\text{-}2002,i}$ is an indicator variable representing whether child *i*'s parent experienced an activity-limiting health event between the 1997 and 2002 measures of the child's skill level; $Event_{<1997,i}$ is an indicator variable representing whether child *i*'s parent experienced an activity-limiting health event prior to the 1997 measure of the child's skill level; and $\mathbf{X}_{1997,i}$ is a vector of observable child and family characteristics measured until the 1997 CDS interview and indicator variables for the parent experienced a health event that did not significantly limit her activities.

The coefficient of interest in the above estimating equation is β_3, the coefficient for children with a parent experiencing an activity-limiting health event between the CDS interviews. β_4 is not interpretable as an effect of lagged health events on skill levels, due to the fact that this estimate incorporates not only any current effects of the health event on the child's skill level, but also any difference from the rate of change for older effects, β_1^{t-1}, as described above.

The PSID includes vast amounts of information to include in the vector, $\mathbf{X}_{1997,i}$. The covariates used in the current analysis include information on the child, parents, and household. Table 1.4 lists the covariates included in $\mathbf{X}_{1997,i}$. Importantly, the control variables include indicators for several cognitive and emotional developmental problems of the child, a wide array of demographic characteristics, and information on the household environment prior to the parental health events. Demographic measures and characteristics determined at or near birth include birth weight, sex, race, birth order, developmental disorders (mental retardation, learning disability, developmental delays, and autism), and early life health indicators (breast fed, premature birth, admission to NICU). Information on the household and parents relates to many lagged investments including income, an index measure of the home environment (HOME-SF), single- vs. two-parent household, home ownership, money for necessities (food), maternal education and age at birth, and others. This broad array of covariates available in the PSID and PSID-CDS help to control for heterogeneity between families with and without parental health events.

Table 1.5 reports coefficient estimates of equation (11) on the cognitive (WJ-R Applied Problem) and non-cognitive (BPI) outcome measures. The table reports two coefficient estimates for the separate regressions identifying parental health events as either the onset of an activity-limiting specific health condition or a work limitation.[13] The first coefficient estimate represents the estimated effect of the onset of a parental health condition or work limitation that limits the activities of the parents on the cognitive or non-cognitive dependent variable. The second coefficient estimate is for the lag of the dependent variable. The health conditions include the onset of any condition listed in the top panel of Table 1.1; work limitations include any physical or nervous condition reported to limit the type or amount of work the individual can perform.[14]

The estimated effect of a new activity-limiting health condition, using either definition of a health event, on the child's cognitive test score is small and not statistically different from zero. The onset of a specific condition that limits the parent's activity is estimated to reduce the child's WJ-R Applied Problem test score by 0.045 standard deviations. A newly reported work limitation that considerably alters the respondent's ability to work is estimated to raise the child's cognitive test score by a similar statistically insignificant amount, 0.031 standard deviations.

[13] A listing of all coefficient estimates is available from the author upon request.
[14] Specific conditions include stroke, heart attack, heart disease, high blood pressure, lung disease, asthma, cancer, diabetes, arthritis, memory loss, or emotional and nervous disorders reported to limit the daily activities of the parent "somewhat" or "a lot." Work limitations include limiting the type of work to "can do nothing" or the amount of work by "a lot."

Table 1.4
Additional Covariates Included in Regression Equation

Information on Child	**Information on Household**	**Information on Parents**
Birthweight in ounces	Avg. family income, 1994-1996	Mother's age and square
Male	HOME-SF score in 1997[3]	*Mother's age at birth (<18, 18-19, 20-29, >29)*
White	Number of children in 1997	*Mother's Education*
Black	*Two parent household*	*(HS dropout, HS grad, Some college, Bachelor+)*
Hispanic	*Two biological parent hh*	*Parent has a non-activity limiting health event*
Other Race	*Eat 4+ meals together per week in 1997*	*Parents ever smoke cigarettes*
First born	*Rent (vs. own) home any time 1994-1997*	*Unemployed any time 1993-1996*
Second born	*Ever short of money for food, 1995-1997*	*Out of labor force any time 1993-1996*
Breast fed		*Extra job at any time 1993-1996*
Mental retardation		*Non-native English speaker*
Learning disability		*Speaks non-English language with child*
Developmentally delayed		*Report taking vacation, 1994-1997*
Autistic		
Premature birth (8 weeks or more)		
Time in neonatal intensive care unit		
Age of Child Indicators (3-mo. Span)		

Notes:
1. Data drawn from the Panel Study of Income Dynamics Main Family and Child Development Supplement files
2. Indicator variables shown in italics
3. The Home Observation and Measurement of the Environment-Short Form

Table 1.5

Estimated Effects of Parental Health Events on Children's Cognitive and Non-Cognitive Skill Measures

	Coefficients		
Skills	New Specific Condition	New Work Limitation	Lag of Skill Measure
WJ-R Applied Problem	-0.0451		0.4677***
	(0.0619)		(0.0277)
		0.0309	0.4679***
		(0.0842)	(0.0278)
Behavior Problem Index	-0.1804**		0.4945***
	(0.0762)		(0.0282)
		-0.1655	0.4946***
		(0.1030)	(0.0287)

Notes:

1. Data drawn from the Panel Study of Income Dynamics Main Family and Child Development Supplement files
2. Specific conditions include stroke, heart attack, heart disease, hypertension, asthma, lung disease, diabetes, arthritis, memory loss, learning disorders, cancer, and psychiatric problems reported to limit the parent’s normal daily activities “somewhat” or “a lot”
3. Work limitations are non-specified physical or nervous conditions that limit the type of work a person can perform to “can do nothing” or the amount of work she can perform by “a lot”
4. New Events include the onset of a specific health condition after the 1997 CDS interview and prior to the 2002 interview

The estimated coefficients for either definition of a health event are similar for the BPI dependent variable. The onset of a new specific condition and new work limitation for a parent are estimated to decrease a child's BPI score by 0.18 and 0.17 standard deviations. Although the coefficient estimate for a parental work limitation is not statistically significant, the fact that the coefficient is sizeable and similar to the coefficient for a specific condition suggests that the smaller number of parental work limitations is the driver behind statistical insignificance.

Previous empirical literature examining treatment effects of shocks to children's skill development, described above in Section 2, suggests that effects of parental health events may affect sons and daughters differently. Table 1.6 shows estimated effects of health events when the sample is split into male and female children and regressions are run separately on the two sub-samples. The estimates show that sons appear to be negatively affected when a parent suffers from a health event, whereas daughters are less negatively affected.

The onset of a new specific health condition in a parent is estimated to reduce the cognitive and noncognitive measure of sons' skills by 0.17 and 0.31 standard deviations. These estimates are statistically and meaningfully significant. The estimates for a new parental work limitation do not indicate a difference in cognitive test scores for male children after the health event, but confirm a sizeable decrease in behavioral outcomes when a parent suffers from a new health event, an estimated reduction of 0.31 standard deviations in the BPI score.

The estimated effects of new parental health events on daughters' cognitive skills suggest that parental health events do not affect this outcome. Statistically insignificant coefficients of 0.02 and 0.03 standard deviation changes are estimated for new specific conditions and work limitations. The estimated effects of parental health events on daughters' behavior outcomes are negative but muted compared to the estimates for sons. The estimated effects of a new parental

Table 1.6

Estimated Effects of Parental Health Events on Children's Skill Measures by Sex

		Coefficients for Sons	
Skills	New Specific Condition	New Work Limitation	Lag of Skill Measure
WJ-R Applied Problem	-0.1618**		0.4584***
	(0.0823)		-(0.0339)
		-0.029	0.4601***
		(0.1250)	-(0.0347)
Behavior Problem Index	-0.3090***		0.4940***
	(0.1083)		-(0.0383)
		-0.3083**	0.4901***
		(0.1474)	-(0.0393)
		Coefficients for Daughters	
WJ-R Applied Problem	0.022		0.4824***
	(0.0940)		-(0.0444)
		0.033	0.4778***
		0.1273	-(0.0443)
Behavior Problem Index	-0.1112		0.5047***
	(0.1106)		-(0.0413)
		-(0.0876)	0.5057***
		(0.1514)	-(0.0412)

Notes:

1. Data drawn from the Panel Study of Income Dynamics Main Family and Child Development Supplement files
2. Specific conditions include stroke, heart attack, heart disease, hypertension, asthma, lung disease, diabetes, arthritis, memory loss, learning disorders, cancer, and psychiatric problems reported to limit the parent's normal daily activities "somewhat" or "a lot"
3. Work limitations are non-specified physical or nervous conditions that limit the type of work a person can perform to "can do nothing" or the amount of work she can perform by "a lot"
4. New Events include the onset of a specific health condition after the 1997 CDS interview and prior to the 2002 interview
5. Clustered robust standard errors in parentheses

specific condition, -0.11 standard deviations, and work limitations, -0.09 standard deviations, are roughly a third of the size of the effects for sons. Neither estimated effect is statistically different from zero at the 0.1 level of significance.

In addition to differential effects for sons and daughters, families may respond differently if a mother becomes ill than if the father becomes ill. A significant number of mothers and fathers suffer from each definition of a health event. Of the 206 children with at least one parent experiencing the onset of a specific health condition that significantly limits the parents' daily activities, 136 and 81 children have a mother and father who experience a specific health condition, respectively. A significant number of children have each type of parent experience a significant work limitation, as well: 57 mothers and 37 fathers.

Table 1.7 displays the estimated effects of maternal and paternal health events. There are no identifiable effects of maternal or paternal health events on the cognitive, WJ-R Applied Problem, test measure. The estimates for maternal and paternal shocks are not statistically different from zero nor are they statistically different from each other. Estimated effects for the children's behavioral outcomes tell a different story. Paternal health events significantly and negatively affect children's behavioral outcomes, estimated reduction in BPI scores of 0.39 and 0.32 standard deviations. Maternal health events are not estimated to reduce the child's behavioral score so dramatically. Using one measure of a maternal health event, onset of a specific condition, provides a point estimate of an effect on the child's score of -0.11 standard deviations. However, using the alternative measure of a health event, a work limitation, the estimated effect on the child's BPI is roughly zero, -0.01. Neither of the estimated effects of maternal health events on children's BPI scores is statistically different from zero. Moreover, the estimated effects for fathers and mothers, using the specific conditions as a health event, are statistically different from each other at the 10% level of significance. The results suggest that paternal health events significantly reduce children's behavioral skill development.

Table 1.7
Effects of Maternal and Paternal Health Events on Children's Skills

		WJ-R Applied Problem	Behavior Problem Index
Specific Conditions			
	Maternal	-0.0007	-0.1105
		(0.0734)	(0.0899)
	Paternal	-0.1365	-0.3893***
		(0.0830)	(0.1219)
Work Limitation			
	Maternal	0.0817	-0.0118
		(0.1094)	(0.1164)
	Paternal	-0.0962	-0.3179*
		(0.1081)	(0.1708)

Notes:
1. Data drawn from the Panel Study of Income Dynamics Main Family and Child Development Supplement files
2. Specific conditions include stroke, heart attack, heart disease, hypertension, asthma, lung disease, diabetes, arthritis, memory loss, learning disorders, cancer, and psychiatric problems reported to limit the parent's normal daily activities "somewhat" or "a lot"
3. Work limitations are non-specified physical or nervous conditions that limit the type of work a person can perform to "can do nothing" or the amount of work she can perform by "a lot"
4. New Events include the onset of a specific health condition after the 1997 CDS interview and prior to the 2002 interview
5. Clustered robust standard errors in parentheses

Previous literature suggests that there are sensitive periods for development across skills. Specifically, Cunha and Heckman (2008) estimate that a sensitive developmental period for cognitive skills occurs earlier in childhood and that noncognitive skill development is more sensitive to investments in later childhood. To investigate whether children of varying ages are affected differently by parental health events, I match the date of onset for parents experiencing an activity limiting specific condition to the children's ages at onset. I divide the children of parent with health events into four categories based on the child's age at onset. These categories represent early childhood, 0 to 4 years; late childhood, 5 to 9 years; early adolescence, 10 to 14 years; and late adolescence, 15 years or older. The evidence suggests that we should see the largest effects of parental health events on cognitive outcomes in the youngest group, early childhood, and on noncognitive outcomes in the second age group, late childhood.[15]

Table 1.8 displays the estimated effects of new specific health conditions for parents by the child's age at onset. There does not appear to be a significant effect on the measure of children's cognitive test scores at any age. The expected period for cognitive sensitivity to parental health events is during the ages of 0 to 4 years. The estimated effect of the onset of a parent's activity health condition during this period is an increase of 0.054 standard deviations. However, the number of children in the sample with a parent suffering onset during this time is small, n = 21, and the effect is imprecisely measured with a large standard error of 0.15. The imprecise estimate does not provide evidence about cognitive sensitivity during this period.

Estimates in the last column of Table 1.8 suggest that children's behavioral outcomes are most negatively affected for children who were aged 5 to 9 years when the parental health event occurred. The estimated effect of a parental health condition occurring during these ages is a reduction in the BPI score of 0.28 standard deviations. This is a period of later childhood when noncognitive skills are expected to be more sensitive to investments. We see a negative estimated effect during young childhood, 0.21 standard deviations, as well. However, the estimated effects are again imprecisely estimated and do not provide conclusive evidence regarding the effects of parental health events during periods outside of late childhood.

[15] A similar age related analysis on health derived parental work limitations is not possible. The PSID does not gather information on when the limitation began. Therefore, I can only identify the onset of the work limitation as a point in time during the two years between the biennial surveys.

Table 1.8
Effects of Parental Specific Health Conditions on Children's Skills by Age of Onset

		WJ-R Applied Problem	Behavior Problem Index
Child Age at Onset	0 to 4	0.0537	-0.205
		(0.1510)	(0.1750)
	5 to 9	-0.076	-0.2784***
		(0.0830)	(0.1040)
	10 to 14	0.0018	-0.0589
		(0.0790)	(0.1080)
	15 or older	0.1138	0.0209
		(0.1990)	(0.2510)

Notes:
1. Data drawn from the Panel Study of Income Dynamics Main Family and Child Development Supplement files
2. Specific conditions include stroke, heart attack, heart disease, hypertension, asthma, lung disease, diabetes, arthritis, memory loss, learning disorders, cancer, and psychiatric problems reported to limit the parent's normal daily activities "somewhat" or "a lot"
3. Work limitations are non-specified physical or nervous conditions that limit the type of work a person can perform to "can do nothing" or the amount of work she can perform by "a lot"
4. New Events include the onset of a specific health condition after the 1997 CDS interview and prior to the 2002 interview
5. Clustered robust standard errors in parentheses

Given the broad range of ailments in the health conditions, I continue the analysis by grouping the specific health events into categories. First, I group together the physical ailments (stroke, heart attack, heart disease, high blood pressure, lung disease, asthma, cancer, arthritis, and diabetes) and the mental ailments (mental loss and emotional, nervous, and psychiatric) and run the estimation on these two types of conditions. Second, I disaggregate the conditions further into vascular ailments (stroke, heart attack, heart disease, high blood pressure), respiratory ailments (lung disease and asthma), arthritis and diabetes ailments, mental ailments (mental loss and emotional, nervous, and psychiatric), and cancer, and obtain estimates for the more narrowly defined groups of health conditions. Table 1.9 provides the estimated coefficients for the disaggregated condition groups.

Broadly grouped as physical and mental conditions, neither type of condition is estimated to affect the children's WJ-R Applied Problem test scores. Furthermore, when disaggregated further, there are no statistically significant estimated effects on this cognitive measure. Two groups of conditions provide near null estimated effects, mental and arthritis/diabetes conditions. One condition group, respiratory, has a positive estimated effect. And two groups of conditions provide negative estimated effects, vascular and cancer. Overall, there is no clear indication that the specific conditions affect the children's cognitive test scores.

Examining effects of the specific condition groups on the children's behavioral outcome measure, both physical and mental conditions are estimated to reduce the child's BPI score by 0.15 and 0.11 standard deviations, though mental conditions are imprecisely estimated. Further disaggregated groups of conditions, except respiratory, that limit the parents' daily activities are estimated to reduce the children's behavioral outcomes. Though imprecisely estimated due to low numbers of observations, there are sizable average reductions in scores of children, whose parents experience mental, vascular, and cancer conditions: -0.11, -0.16, and -0.31 standard deviations, respectively.

Examining the estimated effects of parental health events on children's skill outcomes, the results suggest several conclusions. First, the cognitive outcomes of children in the sample are not significantly affected by the onset of a parental health event; rather, non-cognitive outcomes appear negatively affected by these events, especially by mental, vascular, and cancer health conditions.

Table 1.9

Estimated Effects of Parental Health Conditions on Children's Skills by Condition

	WJ-R Applied Problem		Behavior Problem Index	
Activity Limiting Condition				
New Physical Condition	-0.0600		-0.1491*	
	(0.0620)		(0.0839)	
New Mental Condition	-0.0209	-0.02	-0.1127	-0.1072
	(0.1479)	(0.1531)	(0.1562)	(0.1614)
New Vascular Condition		-0.0656		-0.1558
		(0.0925)		(0.1293)
New Respiratory Condition		0.1068		0.083
		(0.1630)		(0.2509)
New Cancer Condition		-0.298		-0.3126
		(0.2179)		(0.3366)
New Diabetes/Arthritis		-0.0387		-0.0785
		(0.0828)		(0.1055)

Notes:

1. Data drawn from the Panel Study of Income Dynamics Main Family and Child Development Supplement files
2. Specific conditions include stroke, heart attack, heart disease, hypertension, asthma, lung disease, diabetes, arthritis, memory loss, learning disorders, cancer, and psychiatric problems reported to limit the parent's normal daily activities "somewhat" or "a lot"
3. Work limitations are non-specified physical or nervous conditions that limit the type of work a person can perform to "can do nothing" or the amount of work she can perform by "a lot"
4. New Events include the onset of a specific health condition after the 1997 CDS interview and prior to the 2002 interview
5. Clustered robust standard errors in parentheses

Inputs as Dependent Variables

The theory outlined in Section 2 presumes that parental investments into children's skills are a function of parental health. To investigate whether measures of parental investments provided in the CDS are related to parental health events, I regress the investment measures on parental health events and a vector of covariates to identify if these measures are related to parental health events. Specifically, I regress the value of the inputs measured at the second CDS interview, $Input_{2002}$, on the input measured at the first CDS interview, $Input_{1997}$, the indicators for parental health events occurring between the CDS interviews, $Event_{1997\text{-}2002}$, and prior to the first CDS interview, $Event_{<1997}$, the lagged values of cognitive and noncognitive skills, θ^{C}_{1997} and θ^{N}_{1997}, and the large vector of child, family, and household information presented in Table 1.4, $\mathbf{X}_{1997}$:

$$Input_{2002,i} = \beta_0 + \beta_1 Input_{1997,i} + \beta_2 Event_{1997-2002,1} + \beta_3 Event_{<1997} + \beta_4 \theta^{C}_{1997,i} + \beta_5 \theta^{N}_{1997,i} + \boldsymbol{\delta}\mathbf{X}_{1997,i} + \varepsilon_i.$$

The measures of inputs are the HOME-SF score and the amount of weekly parent-child time. The HOME-SF score is an index measuring cognitive and emotional stimulation in the child's home that has been used by numerous researchers as a measure of investment in children's skill development. The HOME-SF score at the second CDS interview has a mean of 17.7 and a standard deviation of 3. Weekly parent-child time is a measure representing the number of hours that a parent participates in any activity with the child over one week. The weekly hours were extrapolated from two-day time diaries, one week day and one weekend day, conducted by the CDS at each interview. The mean number of hours of parent-child time at the second CDS interview is 17.8 with a standard deviation of 13. These inputs are of particular interest. One measure, the HOME-SF, is a commonly used broad index measure of investments into children's skills, and it is of interest to observe how it changes in relation to a parental event that has been estimated to alter children's noncognitive skills. The second measure, parent-child time, is a hypothesized mechanism for parental health and other household changes (i.e. maternal employment) to affect children's outcomes.

Table 1.10 displays the estimated effects of parental health events on the two measures of child investment. The estimated effects of a parental health event, either specific condition or work limitation, on the HOME-SF score is small and insignificant. Although the coefficient point estimates are both negative, the size of the estimates is small; both are less than 0.07 standard deviations. While statistically insignificant, parental health events are estimated to reduce parent-child time by 0.96 hours per week for a specific parental health condition and 1.65 hours per week for a parental work limitation.

Table 1.10

Estimated Effects of Parental Health Events on Inputs into Children's Skills

Skill Inputs	New Specific Condition	New Work Limitation
HOME-SF Index	-0.1451	-0.2045
	(0.2460)	(0.4133)
Parent-Child Time	-1.0068	-1.5606
	(1.2079)	(1.5531)

Notes:

1. Data drawn from the Panel Study of Income Dynamics Main Family and Child Development Supplement files
2. Specific conditions include stroke, heart attack, heart disease, hypertension, asthma, lung disease, diabetes, arthritis, memory loss, learning disorders, cancer, and psychiatric problems reported to limit the parent's normal daily activities "somewhat" or "a lot"
3. Work limitations are non-specified physical or nervous conditions that limit the type of work a person can perform to "can do nothing" or the amount of work she can perform by "a lot"
4. New Events include the onset of a specific health condition after the 1997 CDS interview and prior to the 2002 interview
5. Clustered robust standard errors in parentheses

Heterogeneity in the estimated effects of parental health events on children's skill measures across sons and daughters, maternal and paternal health conditions, and types of health conditions suggests differences in the estimated effects of parental health events on investments are subject to heterogeneity as well. Alteration of these measured investments that corresponds to the significant estimated effects on child outcomes indicates that changing investments, these measures, and other unobserved investments are driving the skill development of children. Table 1.11 presents the coefficient estimates of parental health events for the varying samples (sons and daughters), for the estimated effects of paternal and maternal health events, and across the varying specific conditions examined in Tables 1.6, 1.7, and 1.9, above. Across the range of estimates, there is no consistency or statistical significance in the estimated effects of parental health events on the HOME-SF scores. There do, however, appear to be several large and significant estimates of effects for parental health events affecting the amount of parent-child time.

The first and second panels of Table 1.11 show the estimated effects of health events on the input measures when the sample is restricted to only sons or daughters. Recall that the estimated effects of parental health events on sons' behavioral outcomes were significant at 0.31 standard deviation reductions, using either definition of a parental health event, while parental health events did not have significant estimated effects for daughters' skill measures. Accompanying the estimated reductions in sons' skills, we see that parental health events are estimated to reduce the amount of weekly time that a parent participates in activities with a son by 2.2 and 2.8 hours for parental work limitations and specific health conditions, respectively. However, the estimates suggest that the time parents spend participating in activities with daughters is not affected by parental health events (estimated reductions of 0.3 and 0.6 hours per week).

Table 1.11
Effects of Parental Health Events on Inputs into Children's Skills

	Dependent Variable Inputs	
	HOME-SF Index	Parent-Child Time
Sample = Sons		
New Specific Condition	-0.3239	-2.7861*
	(0.3812)	(1.5529)
New Work Limitation	-0.7057	-2.2318
	(0.6069)	(2.3269)
Sample = Daughters		
New Specific Condition	-0.1351	-0.2805
	(0.3300)	(1.7065)
New Work Limitation	0.468	-0.6127
	(0.4654)	(2.1868)
Full Sample		
Maternal Specific Condition	-0.1968	-1.1674
	(0.2689)	(1.4046)
Paternal Specific Condition	-0.1324	-0.6247
	(0.3910)	(1.8125)
Full Sample		
Maternal Work Limitation	0.0767	-0.5116
	(0.5171)	(1.9973)
Paternal Work Limitation	-0.6178	-5.5134***
	(0.5061)	(1.9734)
Full Sample		
New Mental Condition	-0.3976	-0.492
	(0.4527)	(2.5718)
New Vascular Condition	0.0298	-4.1073**
	(0.4233)	(1.9148)
New Respiratory Condition	-0.0521	5.9587*
	(0.7197)	(3.2635)
New Cancer Condition	-0.0365	-4.9566
	(0.7849)	(4.2879)
New Diabetes/Arthritis	-0.4247	1.522
	(0.3115)	(1.6184)

Notes:

1. Data drawn from the Panel Study of Income Dynamics Main Family and Child Development Supplement files
2. Specific conditions include stroke, heart attack, heart disease, hypertension, asthma, lung disease, diabetes, arthritis, memory loss, learning disorders, cancer, and psychiatric problems reported to limit the parent’s normal daily activities “somewhat” or “a lot”
3. Work limitations are non-specified physical or nervous conditions that limit the type of work a person can perform to “can do nothing” or the amount of work she can perform by “a lot”
4. Clustered robust standard errors in parentheses

The third and fourth panels of Table 1.9 show the estimated effects of maternal and paternal health events on the input measures. From this group of estimates, the effect of paternal work limitations is the only statistically significant or sizeable estimate. However, Table 1.7 showed that paternal health events, work limitations or specific conditions, were related to large reductions in children's behavioral outcomes, greater than 0.3 standard deviations, while maternal health events were not estimated to significantly alter children's skill development. Table 1.11 shows that where reductions in behavioral outcomes were related to paternal events, we also see one indication of reduced investments during a paternal health shock.

The bottom panel of Table 1.11 shows the estimated effects of the disaggregated specific parental health conditions on the measures of inputs. The estimated effects across conditions on the HOME-SF score are too imprecisely estimated to provide any conclusion. However, there are three sizeable estimated effects of conditions on parent-child time. Parental vascular and cancer conditions are estimated to reduce the amount of parent-child time by 4.1 and 4.9 hours per week, close to one quarter of the average weekly time. However, the few cases of parental cancer in the data, 10, imprecisely estimates the effect. Conversely, the onset of a parental respiratory condition, chronic lung disease or asthma, is estimated to increase the amount of time per week that parents spend participating in activities with their children by 6.0 hours. Relating these results to the estimated effects of the disaggregated parental conditions on children's skills in Table 1.9, the conditions for which it was estimated to reduce children's behavior outcomes the most, vascular and cancer, are the conditions estimated to significantly reduce the amount of parent-child time. Furthermore, parental respiratory conditions provided positive, though statistically insignificant, estimated effects of 0.1 and 0.08 standard deviations on the cognitive and noncognitive skill measures, respectively, and a parental respiratory condition that is estimated to increase the amount of parent-child time by 6.0 hours.

The results of Table 1.9 show that the heterogeneity of effects in parental health conditions across sons, daughters, mothers, fathers, and types of health conditions is consistent with heterogeneity of effects in parental health conditions on the amount of time that parents spend participating in activities with their children.

Conclusion

In this paper, I use longitudinal data on parents and children in the PSID to examine how children's skill development is affected by the onset of parental health events. Using two measures of broadly defined health events, the analysis suggests that negative parental health events have small average negative effects on a measure of children's noncognitive skills during late childhood, problem behavior. A larger sample size is needed to precisely measure the average effects on children's skills because of a small average effect and heterogeneity in effects. Heterogeneity in effects has been identified, across several measures, and indicates that parental health events significantly impair noncognitive skill development for sons; negatively affect children when a father is afflicted with a health event; and negatively affect children when the health event is the onset of a vascular or cancerous condition in the parent. The estimates are sizeable at a roughly 0.3 standard deviation decrease in the behavioral outcome. Heterogeneity in results appears to be driven by heterogeneity in changes in skill investments after a parental health event. When parental health events are estimated to create poor behavior outcomes, large reductions in one measure of skill investment—time that parents participate in activities with children—is also commonly found.

The results also confirm previous findings that behavioral outcomes are most sensitive during the period of late childhood. Unfortunately, given the age of the children in the sample, I am not able to confirm a sensitive period for cognitive skill investments. Finally, the estimates are short-term effects and may be remediated by future investments in children's skills. Examination of future information in the PSID and CDS will be able to further identify the lasting effects of parental health events on children's outcome

CHAPTER II

OCCUPATIONAL STATUS AND HEALTH TRANSITIONS

Co-authored with David C. Ribar and Christopher J. Ruhm

Introduction

Empirical research shows that physically demanding jobs are related to lower levels of health. However, these results provide little indication about why health differs across occupations or about how such differences are generated. A particular gap in our knowledge involves how occupations might affect the timing of health changes, especially transitions into and out of poor health. Information on these linkages could improve our understanding of the mechanisms that lead to the association between occupation and health. Towards this end, we examine how an individual's occupational history is related to the probability of *transitioning* between health states. Specifically, we focus on how health transitions are related to employment in blue-collar, white-collar, and service occupations; we also consider differentials related to the physical demands of occupations.

Occupational status could have asymmetric effects on health transitions – for example, some occupations may be associated with relatively high probabilities of downward movements in health but without a corresponding increase in health improvements. Consider the extreme case of irreversible health changes. Occupationally influenced health investments might protect against or mitigate the likelihood that such shocks take place (and so reduce the probability of downwards health transitions) but would have no effect once such shocks occur (and so would be unrelated to the likelihood of health improvements). Alternatively, once an individual experiences a negative (but not irreversible) health shock his occupation may hinder his ability to offset these deleterious effects with investment. The estimation method employed below allows for such asymmetric effects.

Using data on men's occupational and health histories from the 1984 through 2007 waves of the Panel Study of Income Dynamics (PSID), we create summary histories of occupation and health status over a five-year window and examine how these are related to health two years later. Consistent with prior research, the health of blue-collar workers is found to decline with age faster than that of white-collar workers. What is new, however, is that we further show that this is a consequence of blue-collar employees having a greater likelihood of transitioning from very good to bad health but with no difference in the relative probability that they move from bad to very good health. Similarly, periods out of work or in service jobs predict relatively high rates of negative health transitions without an offsetting rise in the relative likelihood of health improvements. These findings suggest that differences in rates of negative health shocks play a primary role in explaining age-related occupational gradients in health. These qualitative results are robust to several sensitivity analyses are unlikely to reflect differential patterns of errors in self-reports of health status. We also show that heterogeneity in occupation-related physical demands may explain some of the observed patterns.

Conceptual Issues and Previous Literature

In models of health capital, individuals make health investments to optimize healthy time available to work and earn income, and this health capital can be used in combination with or as a substitute for financial and traditional human capital (Grossman, 1972; Muurinen and Le Grand, 1985). The health capital framework is also informative when considering health *transitions*, since the stock of health capital at a point in time depends on health in the prior period, investment flows, predictable depreciation in the health stock and (with uncertainty), stochastic shocks resulting from illness, accidents and the like.

This framework identifies several reasons why occupational status may be related to health. First, persons in highly paid occupations have more ability to finance health investments and greater incentives to undertake them (since periods of poor health impose higher opportunity costs). Second, workers in some occupations may have differential access to information related to health behaviors or methods of alleviating health problems. Third, peer effects may be important and could differ across occupations due to variation in coworker characteristics. Fourth, the rate of health depreciation is likely to be heterogeneous, being particularly high, for example, in physically demanding jobs. Finally, the rate of stochastic health events may vary; for instance, negative shocks will be especially common in occupations with high accident rates.

Several of these sources of occupational disparities could affect health transitions differently than overall (average) health status. Most obviously, health shocks due to accidents cause downward movements in health that could either be transitory or permanent (depending on the nature of the injury). Such shocks, if temporary, increase the volatility of health but need not change long-run average status. In this case, occupations with high accident rates will be characterized by large frequencies of both favorable and unfavorable health transitions. Conversely, accidents that permanently reduce health will have asymmetric effects, increasing negative health transitions without a corresponding rise in health improvements.

Economists have recently started to examine how occupational status and health are related. Fletcher and Sindelar (2009) show that entry into the labor force initiated with a blue-collar (rather than white-collar) job, is associated with significantly lower health at older ages – equivalent to an average seven year increase in age (for persons 30 and older) in OLS models and an even greater amount in IV specifications. However, mechanisms for this relationship are not examined: the maintained hypothesis is that a person's first occupation sets the trajectory of future job conditions, income, and consumption patterns, which affect health. Fletcher, Sindelar and Yamaguchi (forthcoming) provide evidence that exposure (during the previous five years) to physically demanding jobs and work-related environmental hazards are cumulatively harmful to health: a one standard deviation increase in physical demands is associated with a health decrement for nonwhite men equivalent to a two-year reduction in schooling or four additional years of age (with smaller effects for white males). Cross-sectional analyses for the U.S. (Case and Deaton, 2005) and Canada (Choo and Denny, 2006) indicate that health depreciates faster with age for individuals in manual than non-manual occupations, suggesting that occupations have cumulative effects on health and alter its trajectory over the life course.

However, prior research does not examine how occupational status is related to health transitions. The study of such transitions, which we undertake, is interesting in its own right and potentially informative for understanding differences in age-related health gradients. As discussed, blue-collar jobs are likely to have relatively high rates of accidents. These could result in large but temporary deteriorations in health – implying relatively high probabilities of both entering and exiting poor health – or permanent health decrements, so that blue-collar workers disproportionately transition into but not out of poor health. Alternatively, downward mobility in health might be similar across occupations, but blue-collar workers might have more difficulty restoring good health, resulting in a relative deterioration for them at older ages. Our analysis focuses on examining these potentially asymmetric health transitions across occupations. For the most part, we will not explain why the transitions differ – that represents an important topic for future research. However, we will provide some indication of the role played by the physical job demands.

Methodology

We estimate dynamic models that allow us to examine how occupational status is differentially (and possibly asymmetrically) associated with transitions from better to worse health and vice versa. Let h_t represent self-reported health status in year t for a given person. Most of our analyses consider a binary indicator where h_t takes a value of one if the person reports being in "good," "fair," or "poor" health (which we label below as "bad" health) and zero if the person reports being in "very good" or "excellent" health (denoted as "very good" health). h_{ave} is average self-reported health measured over some previous period (t, t-2 and t-4 in most of the analysis); OCC_{ave} is a vector that representing either occupational history over the five-years ending in period t, or particular characteristics of that history; X_t is a vector of observed and possibly time-varying personal characteristics; and ε_t is an error term that encompasses unobserved characteristics. The basic model we estimate is described by:

$$h_{t+2} = \delta h_{ave} + \theta OCC_{ave} + \gamma(OCC_{ave} \times h_{ave}) + \beta' X_t + \epsilon_{t+2}. \quad (1)$$

In (1), estimated values of δ, θ, and γ indicate how health at time t+2 is related to the person's initial health status and occupational history.

Models that incorporate occupational histories have been estimated in previous studies; however, our specifications further allow occupational status to have different associations with transitions into and out of bad health. For people with a recent history of very good health, θ describes how occupational status is associated with downwards health transitions. For people with a history of bad health, δ, θ, and γ indicate how occupational status is associated with movements into better health. The interpretations can be more complicated because h_{ave}, which averages health status over several years, can take values between zero and one.

We estimate (1) as a linear probability model throughout, for convenience and ease of interpretation.[16] The longitudinal design of the PSID provides the health and occupational history information needed to estimate the model but also leads to multiple observations for most of our sample members. Therefore, the estimates below present robust standard errors clustered at the individual level.

Data

Our data on men's health and careers come from the Panel Study of Income Dynamics, which began surveying "heads" and "wives" of a national sample of 4,800 families in 1968, focusing on the economic and income behavior of the family.[17] The PSID has followed these families, including original sample members and their children when they establish independent households. Interviews were conducted annually through 1997 and biennially thereafter.

In each panel since 1984, the PSID has asked heads and spouses: "Would you say your health in general is excellent, very good, good, fair, or poor?" Self-reported overall health status is a widely used summary measure that predicts subsequent mortality (Idler and Benyamini, 1997; Mossey and Shapiro, 1982) and is correlated with indicators of morbidity (Manor, Matthews, and Power, 2001; Miilunpalo et al., 1997). While the measure has many advantages, there are also limitations that should be kept in mind. One shortcoming that is relevant for studies with employment outcomes is that self-reported health measures sometimes suffer from "justification" bias – reporting health problems to explain poor labor force results (Currie and Madrian, 1999). However, this bias is unlikely to depend upon the type of employment, unlike

[16] Preliminary analysis revealed similar patterns of coefficients and statistical significance when using probit specifications, but the linear probability (LP) coefficients are easier to interpret, especially when including the occupation-health interactions (Ai and Norton, 2003).
[17] Family "heads" are defined as the primary financial contributor to a PSID family, but defaults to the male partner of a female primary financial contributor if the male is a husband or has cohabited with the "wife" for at least a year.

self-reports of health-related work limitations, and the relationship between SHS and objective health measures (like mortality) does not appear to vary between manual and non-manual workers (McFadden et al., 2009).

As described earlier, we dichotomize men's SHS into "bad" health (SHS is good, fair, or poor) and "very good" health (SHS is excellent or very good). Nearly our entire sample is observed to be in very good or excellent health at least once. The use of "good" health as a cut-off means that many of our sample members are also observed in the lower health category; however, the results below are robust to using "fair" health as the dividing line.

We measure a person's health history as a simple average of the binary health indicator over the preceding five years (i.e., the proportion of surveys over a preceding five years when the person reported "bad" health). To accommodate the PSID change to biennial surveying after 1997, our primary measure averages data from t, $t-2$, and $t-4$ (ignoring data from $t-1$ and $t-3$ that are available in some but not all years). For example, if the person reported bad health in two of the three survey periods over the previous five years, the health history variable would equal 0.667. As sensitivity tests, we investigated alternative health history variables including one that contains data for all five years—including periods $t-1$ and $t-3$ when available—as well as shorter three- and one-year histories. These changes did not alter our results.

Our analysis examines how occupational status and the physical demands of occupations are associated with health transitions. To form the relevant measures, we consider reports regarding the occupation of the main job held by the household head at the time of each interview and the main job occupation held one year prior to the time of the interview in the years when biennial surveys were conducted. The original 3-digit occupation codes were reclassified, using the procedures detailed in Appendix A, to distinguish between "blue-collar," "white-collar" and "service" occupations, as well as periods of non-employment. These broad occupational designations are assumed to capture some shared job characteristics, most especially physical demands but also possibly work environments and autonomy in work conditions. “White-collar” occupations mostly include jobs in offices, including managers and professionals, who often have a high degree of autonomy. The “blue-collar” occupations generally include production work and tend to be more physically demanding. “Service” occupations include some physically demanding jobs, such as protective service workers, but also some positions with fewer physical demands, such as personal service workers. Blue-collar and service workers generally enjoy less autonomy than white-collar workers.

These characterizations of positions are inexact. For example, the white-collar category includes sales occupations, which might occur outside an office and involve little autonomy, and the blue-collar category includes machine operators, who might have few physical demands. Because of these issues, we also consider alternative classifications used in previous studies. In some analyses, we follow Fletcher and Sindelar (2009) in considering differences between blue-collar employees and all other workers (i.e., not distinguishing between white-collar and service jobs). In other specifications, we follow Case and Deaton (2005) by considering managers and professionals as one category and combining the remaining white-collar jobs with service occupations into another category.

A more direct way to describe the conditions of employment is in terms of specific job characteristics, rather than occupational groups. The core PSID interviews do not ask about these characteristics; however, it is possible to map occupational codes to characteristics typical of those occupations. We do this for one especially relevant characteristic—the physical demands of the job. Using data from the Dictionary of Occupational Titles (DOT) and methods described in Appendix A, occupations were classified on a five point scale where one indicates “Sedentary” jobs and a five was assigned to those requiring “Very Heavy Work.” Consistent with expectations, occupation-based physical demands were highest in blue collar jobs and lowest in white collar occupations, with service employment being between the two–using the five-point scale physical demands averaged 2.9, 2.5 and 1.6 for blue-collar, service, and white-collar workers in our sample.[18]

For our primary multivariate analyses, we measure the recent history of occupational status or characteristics by taking the average of the relevant year-specific measures over the preceding five years. For example, to describe the recent history of blue collar work, we create a measure that represents the proportion of the previous five years that the person was employed in a blue collar occupation. Similarly, to describe the recent physical demands, we take the average of the physical demand measures over the last five years. In sensitivity analyses, we experimented with slightly shorter and longer averaging windows and found that the results are robust to these changes.

Our multivariate analyses include other relevant explanatory variables. A key determinant of health is a person's age, which we measure in years. To control for racial differences in health, we include binary indicators for being black and for being neither black nor white (the omitted category for these indictors is men who are white). Educational differences are accounted for through binary indicators for: not completing high school, graduating high school (or getting a GED) but without college, attending college but without obtaining a bachelor's degree, and completing a bachelor's degree (or more education). We further distinguish between men who were married and unmarried at the time of the survey and include a general set of year dummy variables to account for trends in economic, social, health, and policy conditions. The log of the family's annual income is also included in some analyses.

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[18] The physical demands variable should be interpreted cautiously because the measure averages some jobs within a three-digit occupational category, because the measure is ordinal rather than cardinal, and because occupational characteristics change over time.

Another issue arising in the PSID is that each year's reports come from one respondent, so that wives may sometimes be reporting the health status of their husbands. Our analyses include a binary indicator for such proxy reporting. We have also conducted analyses that were limited to men who were respondents with no substantial change in the results.

Our initial sample is restricted to 30 to 59 year-old male heads of households observed after the PSID started collecting the self-reported health status information. The lower end of this age restriction allows us to examine occupational effects after individuals have had time to amass appreciable work histories. At the upper end, we stop our observations before most people retire but after most have experienced at least some bad health. Indeed, 79 percent of our sample is reported to be in bad health at least once during the observation period. Our observations are further limited to years in which the men report not being in or having recently served in the armed forces. Finally, we restrict the sample to observations with complete information for seven-year span of health data (from t-4 to t+2) and the other explanatory measures. The final principal analysis sample includes 34,607 person-years of information from 5,611 men. The absence of females from our analysis represents a significant limitation that partially results from the less complete data typically available for them but represents an important topic for future research.

Descriptive Analyses

Table 2.1 lists the means for our analysis variables for all of the person-year observations in our sample and conditionally for men reporting different health histories and transitions. Thirty-nine percent of the person-year observations occurred in years where the men reported being in bad health. When we consider the men's recent histories of bad health (the average from t, $t-2$, and $t-4$), the proportion of recent years of bad health drops slightly to 36 percent, which

Table 2.1: Sample Statistics of Selected Variables

Sample: Health (*t*, *t* +2)	Full Sample	Bad(0,0)	Bad(0,1)	Bad(1,1)	Bad(1,0)
Health					
"Bad" health in period *t*	0.386	-	-	1	1
	(0.006)	-	-	-	-
Recent history of bad health	0.364	0.081	0.243	0.818	0.605
	(0.005)	(0.002)	(0.004)	(0.004)	(0.005)
Recent occupational history					
Blue-collar	0.386	0.335	0.452	0.423	0.445
	(0.007)	(0.008)	(0.010)	(0.010)	(0.010)
White-collar	0.444	0.555	0.398	0.278	0.389
	(0.007)	(0.009)	(0.010)	(0.007)	(0.010)
Service job	0.063	0.062	0.070	0.076	0.070
	(0.003)	(0.004)	(0.005)	(0.005)	(0.005)
Not employed	0.107	0.049	0.081	0.222	0.096
	(0.003)	(0.002)	(0.005)	(0.008)	(0.006)
Physical Demands	2.232	2.104	2.315	2.417	2.317
(Employed only)	(0.004)	(0.014)	(0.016)	(0.017)	(0.017)
Individual Characteristics					
White	0.707	0.800	0.657	0.589	0.650
	(0.007)	(0.008)	(0.010)	(0.012)	(0.011)
Black	0.261	0.173	0.312	0.373	0.311
	(0.007)	(0.007)	(0.010)	(0.012)	(0.011)
Other race	0.032	0.027	0.031	0.038	0.038
	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)
Age	42.3	41.2	42.1	44.3	42.1
	(0.096)	(0.123)	(0.147)	(0.162)	(0.158)
Less than HS	0.136	0.062	0.160	0.243	0.167
	(0.005)	(0.004)	(0.008)	(0.011)	(0.009)
HS graduate	0.366	0.324	0.392	0.413	0.401
	(0.008)	(0.010)	(0.011)	(0.012)	(0.011)
Some college	0.228	0.243	0.232	0.199	0.226
	(0.007)	(0.009)	(0.009)	(0.010)	(0.009)
Bachelor's degree	0.270	0.371	0.215	0.145	0.206
	(0.007)	(0.010)	(0.009)	(0.009)	(0.009)
Married	0.860	0.881	0.852	0.820	0.854
	(0.004)	(0.005)	(0.007)	(0.008)	(0.007)
Household income	70894	84816	64838	51600	64697
	(997)	(1649)	(1044)	(889)	(1121)
Person-years *n* =	34,607	16,893	4,359	9,750	3,605

Note: Table 2.1 shows the average values of selected characteristics for a sample of 5,611 30-59 year old men in the Panel Survey of Income Dynamics, 1988-2005. Clustered standard errors are in parentheses.

is consistent with health gradually worsening with age.[19] Our sample is composed mostly of observations for white-collar workers (44 percent) and blue-collar workers (39 percent), with relatively few observations of service workers (6 percent) or non-working men (11 percent). The demographic composition reflects the initial design of the PSID, which oversampled poor households in its first sample in 1968. In particular, black men are over-represented and males who are neither black nor white are under-represented. The average age is 42 years, and more than five-sixths of the observations are of married men. The sample includes men with a range of educational attainments.

Considering health status in periods *t* and *t* + 2, approximately half of the observations represent continuations of very good self-reported health (16,893 out of 34,607), just over a quarter of the observations come from continuations of bad health, leaving a quarter that represent transitions between the health states. Thus, while changes in reported health status are less frequent than continuations, there are still a substantial number of transitions. In particular, there were 4,359 transitions from very good health to bad health, which implies a transition rate of 21 percent, and 3,605 transitions from bad health to very good health, which implies a transition rate of 27 percent.

Several occupational associations are also apparent in Table 2.1. Men with recent histories of blue-collar work are under-represented in the observations with continuations of good health but over-represented in other health patterns. This indicates that blue-collar work is associated with a higher rate of transitioning to bad health and with being in bad health but not with moving into very good health. In contrast, white-collar workers are over-represented in the observations with continuations of very good health and under-represented in those with continuations of bad health. The pattern suggests that white-collar workers have lower rates of

[19] Other things held constant, there is a smaller chance that the men will be in bad health four years prior to the current interview year than in the interview year itself.

transitioning into bad health and higher rates of moving into very good health. The representation of service workers does not vary substantially across the transition groups, suggesting that service jobs are not strongly associated with health or health transitions. The pattern of results for the recent histories of physically-demanding jobs is consistent with those for the broad occupational categories. Workers continuing in very good health had the least physically-demanding recent job histories; those continuing in bad health had the most physically-demanding employment histories. In the next section of the paper, we re-examine these relationships using multivariate models that account for possible confounding influences of other observed characteristics.

Multivariate Results

In the following, we discuss the estimated effects of occupational history on the probability of transitioning into and out of bad health from a history of very good and bad health, respectively. Estimates from four linear probability specifications are reported in Table 2.2. As described in equation (1), each includes controls for the recent health history, the recent occupational history (the proportion of years working in blue-collar jobs, service jobs, and not working), and interactions of the health and occupational histories. All of the models also control for age, race, marital status, and general year effects, although for brevity, we only report the coefficients for age. All columns except for the second also hold constant educational attainment. The third and fourth columns also control for household income, with the last column also adding occupation-specific age profiles.

Table 2.2. Selected Results from Linear Probability Models of the Probability of "Bad" Health

	(1)	(2)	(3)	(4)
Recent history of bad health	0.718***	0.728***	0.714***	0.719***
	(0.012)	(0.012)	(0.012)	(0.012)
Blue-collar occupation	0.048***	0.075***	0.043***	0.037***
	(0.009)	(0.008)	(0.009)	(0.012)
Service occupation	0.036*	0.057***	0.030*	0.011
	(0.016)	(0.016)	(0.016)	(0.022)
Not employed	0.127***	0.150***	0.096***	0.136***
	(0.025)	(0.025)	(0.025)	(0.028)
Blue-collar occupation ×	-0.060***	-0.059***	-0.060***	-0.064***
recent history of bad health	(0.017)	(0.016)	(0.017)	(0.017)
Service occupation ×	-0.018	-0.020	-0.020	-0.028
recent history of bad health	(0.027)	(0.028)	(0.027)	(0.029)
Not employed ×	-0.073**	-0.069**	-0.069**	-0.066**
recent history of bad health	(0.029)	(0.029)	(0.028)	(0.030)
Age	0.003***	0.003***	0.003***	0.002***
	(0.000)	(0.000)	(0.000)	(0.001)
Blue-collar*Age				0.001
				(0.001)
Service*Age				0.002
				(0.002)
Not employed*Age				-0.001
				(0.001)
Additional Controls				
Education	Yes	No	Yes	Yes
Household Income	No	No	Yes	Yes
Calculated associations of characteristics with transitions to very good health				
Blue-collar occupation	0.012	-0.016	0.017	0.027
	(0.014)	(0.013)	(0.014)	(0.019)
Service occupation	-0.017	-0.037	-0.010	0.018
	(0.022)	(0.021)	(0.022)	(0.032)
Not employed	-0.054***	-0.081***	-0.027	-0.070***
	(0.015)	(0.015)	(0.015)	(0.025)

Note: Table displays coefficients from linear probability models where the dependent variable is "bad" health in period $t+2$. The models were estimated using 34,607 person-year observations on 5,611 men from the 1988-2005 waves of the PSID. All models include controls for race, marital status, proxy respondents, and general year effects. The coefficients for the transitions to very good health are the calculated by combining the coefficients for health and occupational histories and their interactions. Robust standard errors, clustered by individual, are shown in parentheses.

In these specifications, the coefficients on the uninteracted occupational measures can be directly interpreted as the conditional associations of occupational status with transitions from very good health to bad health. The corresponding associations of occupational status with transitions in the other direction, from bad health to very good health, can be determined by combining the coefficients on recent health status, recent occupational histories, and their interactions. While these coefficients are reported, we have also combined the relevant coefficients into summary measures of how of occupational status predicts transitions into very good health. These are reported in the bottom panel of Table 2.2.

The estimates from the multivariate specifications are broadly consistent with occupational differences in health transitions from the descriptive analyses. In the specification reported in the first column with educational controls but no income controls, men whose recent experience has been entirely in blue-collar work are estimated to face a 4.8 percent greater chance of transitioning from very good to bad health than men whose recent experience has been entirely in white-collar work. Men whose recent expericence has been entirely in service work rather than white-collar also face higher rates of transitions into bad health, as do men who have not been employed over the preceding five years.[20]

Estimates of the occupational differences in probabilities of transitioning between bad and very good health (which are calculated by taking the negative of the sum of the interacted and uniteracted occupational effects) are reported are reported in the lower panel of Table 2.2. Results from the specification in the first column indicate that the probabilities of exiting bad health for men with histories of blue-collar and service work do not differ significantly from the probabilities for those with histories of white-collar work. However, men in bad health who have

[20] The estimated effect of non-employment is difficult to interpret for two reasons. First, non-employment is highly endogenous to self-reported health for men in the sample age range (Currie and Madrian, 1999). Second, for observations with any observed non-employment (in the previous five years), fewer than 5 percent are non-employed for more than half of the period.

not been employed appear to be less likely to transition back to very good health than other men.

These patterns of results are robust when we alter the controls in the models. The relative probabilities of downwards health transitions for blue-collar, service and nonemployed workers become stronger compared to those in white-collar jobs when education is excluded from the model (column 2). There are also changes in the estimated occupational differences in the probabilities of transitioning from bad health to very good health, although there are no changes in the statistical significance of the results. Positive correlations between education and health have been widely observed (Grossman and Kaestner, 1997), and it seems likely that schooling provides some protection against downwards movements in health. Given that education is correlated with occupational status, it is not surprising that the predicted occupational effects on negative health transitions become stronger when deleting education controls. Because the general implications do not change when excluding education as a covariate, we follow the previous empirical economics literature and control for education in all other specifications.

The third column of Table 2.2 lists results from a specification that adds the log of total household income in period *t* as a control variable.[21] The estimated occupational differences in the probability of transitioning from very good health to bad health are slightly smaller than the estimated differences in the first column. Men with a history of blue-collar employment are still 4.3 percentage points more likely to move from very good to bad health, relative their white-collar counterparts. Similarly, the estimated difference for men with a work history in service jobs is relatively close to the original estimate, at an increase of 3.0 percentage points in the probability of entering bad health. As for exiting bad health, there are still no statistically significant differences between men with blue-collar or service occupational histories and those in white-collar jobs, while the differential associated with non-employment shrinks in size and

[21] We have also used total household income averaged over the 5-year period without a substantive change in results.

loses statistical significance. In general, results from this specification indicate that income plays a partial mediating role between occupational status and health outcomes but that other sizeable associations still remain.

Specification (4) adds interactions between the employment history variables and a linear age trend, allowing health trajectories to differ with age across occupational types. If occupational status is associated with the general age profile of health, we might expect to see differences in these interactions rather than the transition terms. However, the interactions between occupational status and age are not statistically significant and occupational differences continue to appear in health transitions.

Sensitivity Tests

We have re-estimated our models using several alternative specifications of our health and occupational history measures. Selected results from these alternative specifications are reported in Table 2.3. The specifications in Table 2.3 generally have the same auxiallary controls as the first specification in Table 2.2 (i.e., they include controls for age, race, marital status, proxy reporting, education, and year effects but omit controls for income or occupation-specific age effects). Table 2.3 reports coefficients on the differences between workers in blue-collar and white-collar occupations in their transitions into and out of bad health.

The first three specifications in Table 2.3 incorporate alternative measures of our health history variable. Recall that for reasons of consistency over different years of the PSID, our recent health history measure includes observations from periods $t-4$, $t-2$, and t but not periods $t-3$ or $t-1$, even when those observations are available. The initial specification in Table 2.3 includes all of the available observations in the health history measure. However, there is almost no change in the estimated results.

Table 2.3: Predicted Difference in Probability of Health Transitions for Blue-collar Versus White-collar Occupations

Econometric Specification	Transition to Worse Health Status	Transition to Better Health Status
(1) Health History included in all available years	0.042*** (0.009)	0.015 (0.014)
(2) Health History in *t* & *t*-2 Only	0.055*** (0.010)	0.004 (0.014)
(3) Health History in *t* only	0.066*** (0.011)	-0.008 (0.015)
(4) Restrictive Definition of "Bad" Health	0.015*** (0.004)	0.012 (0.040)
(5) Health Transition in t+2 or t+4	0.081*** (0.014)	0.019 (0.019)
(6) Blue-collar vs other occupation	0.041*** (0.009)	0.018 (0.013)
(7) Blue-collar vs professional	0.051*** (0.010)	0.011 (0.016)
Non-blue-collar vs professional	0.026*** (0.010)	-0.011 (0.020)
(8) Physical demands	0.016*** (0.0053)	0.004 (0.0015)

Note: Specifications in rows (1)-(5) show the difference in the predicted probability of transitions into or out of bad health for men with a 5-year history of blue-collar work versus an equal period in white-collar work. Specifications in rows (6)-(8) show the difference in the predicted probability of transitions into or out of bad health for men with a 5-year history in the listed occupations. The coefficients are from linear probability models estimated using 34,607 person-year observations for 5,611 men from the 1988-2005 waves of the PSID. All models include controls for race, educational attainment, marital status, proxy respondents, and general year effects. Model (1) includes health history variables in years t-1 and t-3 in all years these are available. Models (2) and (3) measure health history over shorter time periods, and specification (5) models bad health that occurs in either t+2 or t+4. Specification (8) refers to a one-point change in the physical demands score over five years. Robust standard errors, clustered by individual, are shown in parentheses.

In the next two rows, we report results from models that use different reporting lengths to define the person's initial health status. One reason for combining several years of health data into a single summary measure is to reduce some of the noise associated with the wave-to-wave measures. However, the resulting summary measure may introduce problems of its own by including health reports from several years ago that may not be relevant at the time of the interview. Also, if an individual is in bad health for the full time of the five-year window, it may be the case that the health persistence is too strong to identify any differences across occupational types. To investigate differing health histories, we consider two specifications that use shorter health history measures: one specification uses data from periods $t - 2$ and t, while the other uses information only from period t. Our findings remain robust. The estimated differences between the probabilities of blue-collar and white-collar workers transitioning to bad health become slightly stronger when we condition on shorter histories of health. The estimated differences in the probabilities of transitioning to very good health do not change. The change in relative probability of transitioning into but not out of bad health provides evidence against one concern of this study, occupationally related measurement error in self-reported health status. If the level of measurement error in self-reported health, uninformative movement between health categories, is greater for individuals in blue-collar occupations then we might expect to see greater probabilities of transitioning between better *and* worse health states when we condition on shorter measures of health history for this group. The fact that we see a greater probability of transitioning into bad health but no change in the probability of transitioning out of that status when the shorter health history measures are used suggests that differences in the probability of transitions are not simply due to the correlation of measurement error in the health variable with occupational types.

The next row in Table 2.3 lists results from a specification that defines "bad" health at a different point in the SHS scale. In particular, we re-specify the cut-off for bad health more stringently as reporting "fair" or "poor" SHS, rather than "good," "fair," or "poor." Even with the stricter definition, blue-collar workers are estimated to face a higher risk of a negative health transition than white-collar workers. Consisent, however, with the lower overall probability of experiencing "fair" or "poor" health, the size of the differential is reduced from our previous specifications. The differences between blue-collar and white-collar workers in their probabilities of transitioning to better health remain statistically insignificant but mainly due to an imprecise estimate.

The fifth row of Table 2.3 lists results from a specification that uses bad health in either period $t + 2$ or $t + 4$ as the dependent variable, rather than bad health in only period $t + 2$. The additional time to switch health states increases the differences between white-collar and blue-collar work histories in the probability of entering bad health from very good health. Yet, there is still no discernable difference between the probability of exiting bad health for men with blue- and white-collar work histories.

The remaining rows of Table 2.3 report results from models that use alternative occupational history measures and contrasts. The first of these specifications drops the controls for service occupations. This has the effect of combining service workers and white-collar workers into a single (omitted) category. A similar contrast was examined by Fletcher and Sindelar (2009) in their study of initial occupational choices. The change in the occupational measures has almost no effect, however, on the estimated associations. The stability of the estimates most likely results from the very low incidence of service work in our sample.

In the seventh row of Table 2.3, we list estimates from a model that combines service, sales, and administrative workers into a single occupational category. Thus, the omitted occupational group in the models becomes a narrower group of professional and managerial workers. Once again, however, there are few substantive changes in the results.

The final row in Table 2.3 lists results from a regression that replaces the blue-collar and service occupational measures with the five-year average physical demands variable. The results confirm the previous findings that more manual occupations are related to a greater probability of transitioning into bad health given a history of very good health and no significant difference in the probability of transitioning into better health from bad health.

The variables for occupational histories and physical demands are measured in different units; however, it is possible to make a rough comparison of the estimated effects. The average physical demands of a blue-collar occupation in our sample are 1.3 units greater than the average physical demands of a white-collar occupation. If we apply this adjustment factor, five years of employment with the average physical demands of a blue-collar job would increase the probabilty of transitioning to bad health by 2.1 percentage points relative to employment with the average physical demands of a white-collar job. The calculation indicates that physical demands can account for almost half of the differential in transitions between very good and bad health between blue- and white-collar workers.

Conclusion

We use longitudinal data on men's health and occupational histories, from the PSID, to examine how occupational status is asociated with health and health transitions. Previous research indicates that health varies by occupation and that this heterogeneity increases with age. However, since health does not not simply decline over the life-course—with both health decrements and improvements occurring frequently—we estimate models that identify relationships between occupational history and the probabilities of transitioning between both better and worse health for U.S. working age males.

The results show that a recent (five year) history of blue-collar employment predicts a four-to-five percentage point increase in the probability of moving from very good ("very good" or "excellent") into bad ("poor", "fair", or "good") self-assessed health, relative to white-collar employment. However, there are no indications that blue-collar work differentially affects the probability of transitioning out of worse health. Education and income are positively related to health, as in previous studies, but their inclusion does not eliminate the observed occupational effects.

These findings are robust to a series of sensitivity analyses and do not appear to reflect errors in the reporting of self-assessed health. In particular, we estimate specifications that shorten the measured health histories from five years to either three years or one year. Conditioning on shorter health histories should increase measurement error, since averaging occurs over fewer years, and is likely to then increase the likelihood of reporting error based health transitions. Consistent with this, we do see a rise in the relative probability that blue-collar workers transitions into poorer health when using shorter occupational histories. However, there is no corresponding indication that they are more likely to move from bad to very good health, as the differential reporting error explanation would predict.

Our findings suggest that blue-collar workers "wear out" faster with age because they experience more negative health shocks than their white-collar counterparts. There is no evidence that they have greater difficulty in recovering from given shocks, nor is there a strong indication that they regain health more quickly or completely following them. Future research could fruitfully examine mechanisms underlying this occupational heterogeneity. An obvious possibility is that blue-collar workers are more prone to accidents or job-related physical traumas. Indeed, our analysis suggests that physical job demands can account for around two-fifths of the difference in the transition rates of blue-collar versus white-collar workers.

Important caveats should be kept in mind when interpreting our results. Most importantly, endogeneity could be problematic if workers with histories of blue-collar employment have faster health declines than those in white-collar occupations for reasons that are not occupationally related or observed. The inclusion of additional covariates and the use of instrumental variables methods or other identification strategies in future work would be helpful for examining the consequences of such occupational selection. Second, dichotomization of self-reported health status limits our findings to a subjectively chosen threshold and implies that we potentially lose information about movements into or out of more extreme health states. Third, during an era when female employment rates are approaching or exceeding those males and the occupations in which they work are becoming increasingly diverse, an extension of this research to consider women's occupational histories should be pursued.

CHAPTER III

THE COMPLEMENTARITY OF SCHOOL AND WORK IN HUMAN CAPITAL PRODUCTION

Co-authored with Jeremy Bray

This research was conducted with restricted access to Bureau of Labor Statistics (BLS) data. The views expressed here do not necessarily reflect the views of the BLS.

Introduction

Numerous empirical studies have examined whether the outcomes of youths who work while enrolled in school are better or worse than youths who exclusively attend school. The policy influence of this line of research, however, is limited to whether in-school work should or should not be encouraged to improve the outcome. More efficient and informed policy can result if we examine how these inputs, school and work, interact to produce human capital. By focusing on the production of human capital we may better learn optimal inputs or combinations of inputs to maximize efficiencies in producing human capital. This paper contributes to the literature by developing a theoretical and accompanying empirical model to identify if school and work are complements or substitutes in human capital production—how undertaking these activities together affects the productivity of each. Moreover, we examine if the complementary nature of in-school work differs across school levels or student job types.

The standard Mincerian wage equation posits that schooling and work experience are the human capital inputs that produce wages with each input providing positive effects. However, there has been some disagreement about whether work during school positively affects future wages, a measure of human capital. Multiple reasons can explain this lack of consensus; but, the applied literature has lacked the theoretical structure necessary to identify the mechanisms driving differences in wages. Most studies estimate reduced form wage equations with a measure of school-time employment as a right hand side variable. While providing useful correlations, the models estimate black box treatment effects that do not provide easily interpreted effects and leave researchers to speculate on the mechanisms causing the estimate. To substantially improve our knowledge of the potential benefit or harm of in-school employment we must focus on the flow of human capital rather than the ultimate stock. By studying the flow of human capital we gain a better understanding of how human capital is efficiently formed.

Two related strands of literature exemplify the benefits of examining production flows rather than black box treatment effects. First, examining the dynamic nature of children's human capital development has led to a dramatic increase in our knowledge and policy conclusions. For instance, we now know that heritability plays much less of a role in children's skills and home investments much more. We also know skills are self-productive, dynamically complementary, cross-fertilizing, and that there are sensitive periods (ages) of development for differing types of skills (Cunha, Heckman, Lochner, and Masterov, 2006). With this knowledge, implications abound in policy.

Second, studies of the relationship between education and health production lead to the conclusion that efficient policy can only be made by identifying *how* education affects health and not by identifying the total causal effect of education on health.[22] For example, if education simply increases the allocative efficiency of health inputs—more educated individuals have better information on the productivity of health inputs—then policies designed to increase public health awareness may be more efficient than policies designed to increase education levels of the population.

Much like the examination of human capital development in children and the effects of education in producing health, the study of in-school work should examine *how* working while enrolled in school affects human capital creation. In order to do so, we follow the framework of Bray (2005) who examined how alcohol consumption can alter wages by affecting the productivity of school and labor market experience as human capital inputs. Bray's model showed that one can identify the cross-partial derivative of human capital inputs and thus whether or not the inputs are complements or substitutes in the production function. We follow this notion to develop a theoretical and accompanying empirical model that identifies the sign of the cross-partial derivative of work and school in production of human capital for individuals in the National Longitudinal Survey of Youth 1997 (NLSY97). In doing so, we are the first to specifically examine how in-school work alters the productive efficiency of each input. The results show that, on average, work and school are indeed complementary in the production of human capital. However, examination of in-school work at differing schooling levels or across different student occupations suggests that certain types of work and school are complementary when simultaneously undertaken while others are substitutes. An important implication is that human capital production may be increased not only by the selection of inputs but also the timing of inputs.

[22] See Grossman and Kaestner (1997), Cutler, Lleras-Muney, and Vogel (2008), and Kenkel (2000) for reviews and discussion.

The endogeneity of school, work, and in-school employment are addressed by simultaneously estimating the dynamic school, work, and in-school work decisions, leading to the stock of each type of experience, along with the wage equation in which we measure their effects. We use the Discrete Factor Method (DFM) to estimate a discrete distribution of an unobserved factor, common among all equations in the dynamic system. By summing over the probability weighted points in the distribution we remove the problematic correlation between the demand for school and labor and the error term in the wage equation and can identify the effects of their influence on wages.

Previous Literature

Previous literature examining the effects of school-time employment on human capital indicators, including wages, earnings, and unemployment typically finds null to small positive, possibly time deteriorating, treatment effects of school time employment on future outcomes (Ehrenberg & Sherman, 1987; Hakkinen, 2006; Hotz & et al., 2002; Leventhal, et al., 2001; Light, 1999; Marsh & Kleitman, 2005; Meyer & Wise, 1983; Parent, 2006; Ruhm, 1995, 1997; Stern & et al., 1997). However, there is some disagreement among the findings to whether or not work during school positively affects future wages.

One reason for the equivocal findings is a lack of a theoretical model to identify and decompose mechanisms for in-school work to affect future wages. Most studies broadly hypothesize that work during school affects the human capital acquired while in school and estimate reduced form wage equations, without identifying the specific mechanisms measured. The focus, rather, is on statistical identification of the effects of school-time employment on future wages, which is confounded by selection bias.[23] Without some theory driving the empirical strategies, interpretation of the estimated effects estimated is difficult as it is not clear which mechanisms are included in the estimate. A theoretical framework will also help inform future empirical strategies.

Conceptual Issues

In-school employment is thought to alter future wages through, at least, three potential mechanisms: (1) the increase in labor market experience it provides, (2) the effect of in-school work on the education an individual receives,and (3) the complementarity of school and work. The first mechanism simply describes work as an investment in human capital. Common popular support for youth employment is that it provides particularly valuable experience (e.g. builds character, establishes good work ethics, etc.); and, a vast literature provides estimates of the returns to work experience and schooling.[24]

The second and third mechanisms demonstrate two distinctly different ways in which work and school interact if undertaken at the same time. Mechanism (2) suggests that there is change in the allocation of human capital inputs for in-school workers. That is, in-school work may replace school investments during the school year or reduce the total number of years of schooling that would have otherwise been obtained. An accompanying literature addresses this

[23] For instance, individuals employed during school may have familial connections providing access to employment opportunities during school as well as in the future, differing levels of cognitive and non-cognitive skills, or derive a higher satisfaction (less disutility) from employment. If school-time workers self select into working due to these unobserved differences and the unobserved differences also affect wages then estimates from standard regression models will be biased.
[24] See Light and Ureta (1995) and Kim and Polachek (1994) for examples of returns to experience by sex and Bratsberg and Terrell (1998) for returns to experience by race.

mechanism by examining the effects of in-school employment on educational attainment.[25] The consistent findings that school-time workers receive fewer total years of education and that the marginal benefits of these years are reduced with more intensive school-time employment provide support this hypothesis.

This paper is the first, however, to examine the third potential mechanism, if work and school are contemporaneous complements or substitutes in the production of human capital. By identifying if school and work are complements or substitutes in human capital production, we are able to identify how this combination of human capital inputs affects the productive efficiency of work and school.

Theory

A basic multi-period model of wage determination (Mincer, 1974) defines wages in period t as a function of individual demographic characteristics, X_{it}, the stock of human capital at the beginning of period t, K_{it}, and an error term, ϵ_{it}:

$$\ln(wage_{it}) = \beta_0 + \beta_1 X_{it} + \beta_2 K_{it} + \epsilon_{it}. \quad (1)$$

[25] Grades appear to suffer at higher hours of school-time employment (D'Amico, 1984; DeSimone, 2006; Greenberger & Steinberg, 1986; Kalenkoski & Pabilonia, 2010; Lillydahl, 1990; Marsh & Kleitman, 2005; Mortimer & Finch, 1986; Oettinger, 1999; Rothstein, 2007; Stern & et al., 1997) but low hours of school-time employment (i.e. 10-15 hours per week) have shown null or slightly positive effects on grades (DeSimone, 2006; Eckstein & Wolpin, 1999; Ehrenberg & Sherman, 1987; Lee & Orazem, 2008; Oettinger, 1999; Sabia, 2009; Schoenhals, et al., 1998). Furthermore, high school employment has been found to increase the probability of high school graduation (D'Amico, 1984; Lee & Orazem, 2008; Ruhm, 1997) but decrease the probability of attending or graduating from college (Ehrenberg & Sherman, 1987; Lee & Orazem, 2008; Ruhm, 1997).

Suppose that the stock of human capital, *K*, in period *t* is a function of schooling, *s*, labor market experience, *l*, and the stock of human capital held in the previous period,[26]

(2) $$K_t = K_{t-1} + k(s_{t-1}, l_{t-1}),$$

where *k* is an unspecified twice differential production function. By recursively substituting for the previous period's level of human capital, the current stock of human capital can be represented as a function of all previous schooling and labor market experience along with the initial level of human capital such that:

(3) $$K_t = K_0 + \sum_{j=1}^{t-1} k(s_j, l_j).$$

Taking a second-order Taylor series expansion of the human capital production function *k* around a fixed point ($\bar{s}$, $\bar{l}$) equation (2) becomes:

(4) $$\begin{aligned} K_t = K_0 &+ (t-1)k(\bar{s},\bar{l}) + k_s(\bar{s},\bar{l})\sum_{j=1}^{t-1} s_j - (t-1)\bar{s}k_s(\bar{s},\bar{l}) + k_l(\bar{s},\bar{l})\sum_{j=1}^{t-1} l_j \\ &- (t-1)\bar{l}k_l(\bar{s},\bar{l}) + 0.5k_{ss}(\bar{s},\bar{l})\sum_{j=1}^{t-1} s_j^2 + k_{sl}(\bar{s},\bar{l})\sum_{j=1}^{t-1} s_j l_j + 0.5k_{ll}(\bar{s},\bar{l})\sum_{j=1}^{t-1} l_j^2 \\ &- k_{ss}(\bar{s},\bar{l})\bar{s}\sum_{j=1}^{t-1} s_j - k_{sl}(\bar{s},\bar{l})\bar{l}\sum_{j=1}^{t-1} s_j - k_{sl}(\bar{s},\bar{l})\bar{s}\sum_{j=1}^{t-1} l_j - k_{ll}(\bar{s},\bar{l})\bar{l}\sum_{j=1}^{t-1} l_j \\ &+ 0.5(t-1)k_{ss}(\bar{s},\bar{l})\bar{s}^2 + (t-1)k_{sl}(\bar{s},\bar{l})\bar{s}\bar{l} + 0.5(t-1)k_{ll}(\bar{s},\bar{l})\bar{l}^2 \end{aligned}$$

[26] For simplicity I assume that human capital does not depreciate and that the production function for human capital is not period specific.

where subscripted *s* and *l* represent derivatives with respect to schooling and labor.

Substituting equation (4) into (1) produces the following wage equation (5):

$$(5)\quad \ln(wage_{it}) = \beta_0 + \beta_1 X_{it} + \beta_2 K_{i0} + \gamma_1 (t-1) + \gamma_2 \sum_{j=1}^{t-1} s_{ij} + \gamma_3 \sum_{j=1}^{t-1} l_{ij} + \gamma_4 \sum_{j=1}^{t-1} s_{ij} l_{ij} + \gamma_5 \sum_{j=1}^{t-1} l_{ij}^2 + \gamma_6 \sum_{j=1}^{t-1} s_{ij}^2 + \epsilon_{it}$$

where,

$$\gamma_1 = \beta_2\big(k(\bar{s},\bar{l}) - \bar{s}k_s(\bar{s},\bar{l}) - \bar{l}k_l(\bar{s},\bar{l}) + 0.5k_{ss}(\bar{s},\bar{l})\bar{s}^2 + k_{sl}(\bar{s},\bar{l})\bar{s}\bar{l} + 0.5k_{ll}(\bar{s},\bar{l})\bar{l}^2\big),$$

$$\gamma_2 = \beta_2\big(k_s(\bar{s},\bar{l}) - k_{ss}(\bar{s},\bar{l})\bar{s} - k_{sl}(\bar{s},\bar{l})\bar{l}\big),$$

$$\gamma_3 = \beta_2\big(k_l(\bar{s},\bar{l}) - k_{sl}(\bar{s},\bar{l})\bar{s} - k_{ll}(\bar{s},\bar{l})\bar{l}\big),$$

$$\gamma_4 = \beta_2 k_{sl}(\bar{s},\bar{l}),$$

$$\gamma_5 = \beta_2 0.5k_{ll}(\bar{s},\bar{l}),$$

$\gamma_6 = \beta_2 0.5k_{ss}(\bar{s},\bar{l})$, and

$\epsilon_{it} = \eta_i + \rho_{it}$.

The coefficients in equation (5) provide information on the production function. In particular the γ coefficients identify a number of aspects of the human capital production function. The coefficient on the cumulative interactions of schooling and work experience, γ_4, measures the differential return to wages from the work and school inputs from undertaking the activities at the same time rather than separately. Under the straightforward assumption that the effect of human capital on wages, β_2, is positive, the sign of γ_4 indicates the sign of the cross-partial derivative of school and labor in the human capital production function. If the sign of the cross-partial derivative is positive, $\partial^2 k(s,l)/\partial s \partial l > 0$, then the inputs are direct compliments in human capital production; if negative, $\partial^2 k(s,l)/\partial s \partial l < 0$, they are direct substitutes; and independent if $\partial^2 k(s,l)/\partial s \partial l = 0$.[27] Therefore, if school and work are production complements (substitutes) then working while in school increases (decreases) the productivity of each input. If the inputs are independent there is no difference between undertaking the activities together or separately. Additionally, the signs of the second-order derivatives of work and school in the human capital production function, assumed negative, are shown by the sign of γ_5 and γ_6 and the relative ratios of these Hessian elements can be determined. The error term, ϵ_t, contains unobserved individual characteristics, η_i, and mean-zero i.i.d. random shocks, ρ_{it}.

[27] Note that if a production function $f(x,y)$ is homogeneous of degree one and $\partial^2 f(x,y)/\partial x^2 < 0$ then Euler's Theorem states that the inputs must be direct complements, $\partial^2 f(x,y)/\partial x \partial y > 0$. The assumption that the human capital production function is homogeneous of degree one, however, is tenuous and unlikely to be of consequence for our analysis.

Empirical Equation

The empirical counterpart of equation (5) is:

(6) $$\ln(wage_{it}) = \mathbf{X}_{it}\boldsymbol{\beta}_w + \gamma_{w2}\sum_{j=1}^{t} s_{ij} + \gamma_{w3}\sum_{j=1}^{t} l_{ij} + \gamma_{w4}\sum_{j=1}^{t} s_{ij} * l_{ij} + \gamma_{w5}\sum_{j=1}^{t} l_{ij}^2 + \epsilon_{wit},$$

where $\boldsymbol{X}_{it}$ is a vector of demographic and labor market characteristics and the age effect. The measure of schooling is the sum of years of schooling for the individual. Because schooling is measured in one-year increments the sum of the squared schooling is also one year; therefore, this measure equals the base schooling measure, cannot be estimated, and is omitted from the equation. The measure of labor market experience is the number of hours worked in thousands. And the measure for the interaction is the sum of the interactions, hours of work experience in years in which the individual was enrolled in school.

The estimated parameter of interest is γ_{w4} from the log-linear wage equation (6). However, selection bias occurs if the unobserved characteristics in the error term of the wage equation is related to unobserved factors in the schooling and labor demands. To demonstrate we rewrite equation (6), redefining the error term and introduce labor and schooling demands such that

(7) $$\ln(wage_{it}) = \mathbf{X}_{it}\boldsymbol{\beta}_w + \gamma_{w2}\sum_{j=1}^{t} s_{ij} + \gamma_{w3}\sum_{j=1}^{t} l_{ij} + \gamma_{w4}\sum_{j=1}^{t} s_{ij} * l_{ij} + \gamma_{w5}\sum_{j=1}^{t} l_{ij}^2 + (\eta_i + \rho_{it}),$$

(8) $$S_{ij}^* = \mathbf{Z}_{ij}\boldsymbol{\beta}_S + \beta_{S2}\sum_{q=1}^{j} s_{iq} + \beta_{S3}\sum_{q=1}^{j} l_{iq} + \beta_{S4}\sum_{q=1}^{j} s_{iq} * l_{iq} + \beta_{L5}\sum_{q=1}^{j} l_{iq}^2 + (\nu_S\eta_i + \rho_{Sij}),$$ and

$$(9) \qquad L^*_{ij} = \mathbf{Z}_{ij}\boldsymbol{\beta}_L + \beta_{L2}\sum_{q=1}^{j} s_{iq} + \beta_{L3}\sum_{q=1}^{j} l_{iq}$$
$$+\beta_{L4}\sum_{q=1}^{j} s_{iq} * l_{iq} + \beta_{L5}\sum_{q=1}^{j} l_{iq}^2 + \left(\nu_L\eta_i + \rho_{Lij}\right),$$

where S^*_{ij} and L^*_{ij} are latent demands for school and work, ν_S and ν_L are factor loadings for the unobserved factor in the schooling and labor demand equations relative to its contribution in the wage equation, and the ρ_{it}'s i.i.d. mean-zero random shocks. The stock of human capital at period *t* in the wage equation, therefore, is derived from a dynamic process in which school and labor in all previous periods are inputs. The unobserved heterogeneity in the wage equation is necessarily related to the stocks of schooling and labor experiences because it is also related to the dynamic schooling and labor demands that generate the stocks.

One way to free the wage equation of the problematic correlation is to jointly estimate the school demand, labor demand, and wage equations, assume a distribution for η, and integrate over the probability distribution. Integrating η out of the system will leave the school, labor, and wage equations independent and the joint probability is estimable without bias. However, assuming a distribution for the unobserved factor is precarious. If the distribution is misspecified then so too is the estimating equation, yielding inconsistent estimates.

In this paper, we jointly estimate this dynamic system of labor and schooling choices along with the wage equation; but rather than assume a distribution for η we follow Heckman and Singer (1984) and Mroz (1999) and assume that the cumulative distribution of the unobserved common factor can be approximated with a step function. Specifically, we allow for the distribution of the factor to be represented by four discrete points, rather than a continuous variable, where each mass point represents a "type" of individual.

The DFM assumes that an individual is type *m* with probability *p* such that:

$$\text{Prob}(\eta_i = \eta_j) = p_{\eta,j} \quad p_{\eta,j} \geq 0, \quad j = 1, \ldots, 4, \text{ and } \sum_{j=1}^{4} p_{\eta,j} = 1,$$

where η_j are the points of support for the discrete distributions. We normalize one point of support for the distribution, normalize the factor loading in the wage equation to one, and estimate the remaining points of support, probability weights of each point, and remaining factor loadings. By allowing for discrete types of differing probabilities, we let the functional form of the common factor become flexible and mimic any continuous distribution. Furthermore, integration over the common factor becomes a weighted sum of probabilities that is less computationally intensive.

Exploratory Extended Analyses

There is suggestive evidence that certain types of knowledge are better attained when they are simultaneously applied. Educational curriculums vary across fields of study as do on-the-job training programs over occupations. Technical fields often simultaneously undergo classroom training and application in the form of apprenticeships, cooperative education, or, even project-based schooling. Alternatively, liberal arts students will study in the classroom for a number of years before applying knowledge to their field. These differences suggest that some types of education and experience are best undertaken together, as they may be complementary, while others require prolonged periods of specialization. The implication is that, yes, work and school may be contemporary complements or substitutes, but this will depend upon the nature of education and work that are undertaken.

We hypothesize that some types of work and schooling are contemporaneously complementary while other combinations are substitutes in human capital production. In order to explore this hypothesis we extend the model to examine the relationship between school and work across different schooling levels—high school, two-year college, four-year college, and graduate school—or across different student job types—blue-collar, white-collar, and service jobs. Therefore, we estimate two additional models that identify differences in the complementarity effect across schooling levels and across student occupational types. The measures of in-school work experience in the extended analyses include the sum of in-school work experience at the various education levels or in each job type. By including these extensions we identify if there is an indication that differing types of work and schooling are better suited to complement one another in producing human capital.

Estimating the Likelihood Function

Instead of employing one demand equation for each of the underlying reduced form demand equations, as seen in equations (8) and (9), we estimate separate equations conditional on the individual's status in period *t*, because individuals face different choice sets. For instance, we estimate separate schooling equations for each type of schooling conditional on the educational attainment of the individual at time period *t* (i.e. a high school graduate makes a decision to attend college rather than high school). Similarly, we condition the employment decision on the school decision of the individual (not enrolled in school, enrolled in high school, enrolled in two-year college, enrolled in four-year college, or enrolled in graduate school) as these demand functions will likely have differing coefficients. Additionally, we condition the wage equation on not being enrolled in school in the current period.

The DFM is estimated using aML Version 2 software. Estimating linear equations in a simultaneous equation model using aML has produced unrepeatable results. However, we have been able to verify results of simultaneous equation models with non-linear equations (i.e. probit models). As such, the wage equation and work demand equations are estimated as ordered probits with known thresholds instead of linear functions. The thresholds divide the log wage equation and hours of work, for individuals not enrolled in school, into quintiles, given the wages and hours of work for individuals eligible for these equations.[28] Similarly, the in-school work decision is estimated as an ordered probit. However, demand for in-school work is measured as a single index using a threshold of zero hours, for non-workers, and four additional thresholds dividing the workers in each schooling type into quintiles.

In order to display the likelihood function, we simplify the presentation of the equations such that the vector **X** includes the stocks of schooling, labor, and in-school experience and all additional regressors. The ordered probit of the wage equation is:

$$W_{it}|_{S_{j,it}=0\,\forall\, j} = \begin{cases} 1 \text{ if } w_{it}^{*} = \mathbf{X}_{it}\boldsymbol{\beta}_{W} + \eta_i + \epsilon_{W,it} < \mu_{W,1} \\ 2 \text{ if } \mu_{W,1} < w_{it}^{*} < \mu_{W,2} \\ 3 \text{ if } \mu_{W,2} < w_{it}^{*} < \mu_{W,3} \\ 4 \text{ if } \mu_{W,3} < w_{it}^{*} < \mu_{W,4} \\ 5 \text{ if } \mu_{W,4} < w_{it}^{*} \end{cases} \quad (10).$$

Selection into schooling is observed by the binary variable *S* such that:

$$S_{HS,it}\big|_{HSGrad_{it}=0} = \begin{cases} 1 \text{ if } s_{it}^{*} = \mathbf{Z}_{it}\boldsymbol{\beta}_{HS} + \nu_{HS}\eta_i + \epsilon_{HS,it} > 0 \\ 0 \text{ otherwise} \end{cases}, \quad (11)$$

[28] A sensitivity test was conducted where the wage equation was estimated as an ordered probit with known thresholds dividing the sample into deciles. The results show no qualitative change and estimates based on the simpler division into quintiles is presented.

$$S_{Voc,it}\big|_{HSGrad_{it}=1} = \begin{cases} 1 \text{ if } s_{it}^{*} = \mathbf{Z}_{it}\boldsymbol{\beta}_{Voc} + \nu_{Voc}\eta_i + \epsilon_{Voc,it} > 0 \\ 0 \text{ otherwise} \end{cases}, \tag{12}$$

$$S_{Coll,it}\big|_{HSGrad_{it}=1} = \begin{cases} 1 \text{ if } s_{it}^{*} = \mathbf{Z}_{it}\boldsymbol{\beta}_{Coll} + \nu_{Coll}\eta_i + \epsilon_{Coll,it} > 0 \\ 0 \text{ otherwise} \end{cases}, \tag{13}$$

$$S_{GS,it}\big|_{CollGrad_{it}=1} = \begin{cases} 1 \text{ if } s_{it}^{*} = \mathbf{Z}_{it}\boldsymbol{\beta}_{GS} + \nu_{GS}\eta_i + \epsilon_{GS,it} > 0 \\ 0 \text{ otherwise} \end{cases}. \tag{14}$$

Similarly, selection into hours of in-school work is defined by the latent variable *l**, but is conditional on the schooling level*, j* = *HS*, *Voc*, *Coll*, or *GS*, such that:

$$Labor_{it}|_{S_{it}=j} = \begin{cases} 0 \text{ if } l_{it}^{*} = \mathbf{Z}_{it}\boldsymbol{\beta}_{L_j} + \nu_{L_j}\eta_i + \epsilon_{L_j,it} < \mu_{L_j,0} \\ 1 \text{ if } \mu_{L_j,0} < l_{it}^{*} < \mu_{L_j,1} \\ 2 \text{ if } \mu_{L_j,1} < l_{it}^{*} < \mu_{L_j,2} \\ 3 \text{ if } \mu_{L_j,2} < l_{it}^{*} < \mu_{L_j,3} \\ 4 \text{ if } \mu_{L_j,3} < l_{it}^{*} < \mu_{L_j,4} \\ 5 \text{ if } \mu_{L_j,4} < l_{it}^{*} \end{cases}, \tag{15}$$

where the thresholds are known and are defined such that $\mu_{L_j,0} = 0$ and the remaining cut-points define quintiles for the number of in-school hours for each schooling level.

For individuals not enrolled in school, we estimate separate work decision and hours of employment equations:

$$Emp_{it}|_{S_{j,it}=0\ \forall\ j} = \begin{cases} 1 \text{ if } l_{it}^{*} = \mathbf{Z}_{it}\boldsymbol{\beta}_{Emp} + \mu_{Emp,it} > 0 \\ 0 \text{ otherwise} \end{cases}, \tag{16}$$

$$Labor_{it}|_{S_{j,it}=0\ \forall\ j} = \begin{cases} 1 \text{ if } l_{it}^{*} = \mathbf{Z}_{it}\boldsymbol{\beta}_L + \nu_L\eta_i + \epsilon_{L,it} < \mu_{L,1} \\ 2 \text{ if } \mu_{L,1} < l_{it}^{*} < \mu_{L,2} \\ 3 \text{ if } \mu_{L,2} < l_{it}^{*} < \mu_{L,3} \\ 4 \text{ if } \mu_{L,3} < l_{it}^{*} < \mu_{L,4} \\ 5 \text{ if } \mu_{L,4} < l_{it}^{*} \end{cases}, \qquad (17)$$

where, again, the thresholds are known and defined as the cut-points dividing hours of work for employed non-enrolled individuals into quintiles.

To derive the likelihood function we define vectors for the parameters to be estimated such that:

the vectors of equation coefficients are

$\Theta = (\boldsymbol{\beta}_W, \boldsymbol{\beta}_{HS}, \boldsymbol{\beta}_{Voc}, \boldsymbol{\beta}_{Coll}, \boldsymbol{\beta}_{GS}, \boldsymbol{\beta}_{L_{HS}}, \boldsymbol{\beta}_{L_{Voc}}, \boldsymbol{\beta}_{L_{Coll}}, \boldsymbol{\beta}_{L_{GS}}, \boldsymbol{\beta}_{Emp}, \boldsymbol{\beta}_L)$,

DFM points of support and probability weights are $\boldsymbol{\Gamma} = (\eta_2, \eta_3, \eta_4, p_1, p_2, p_3, p_4)$,

factor loadings for the random effect are

$\boldsymbol{\Lambda} = (\nu_{S_{HS}}, \nu_{S_{Voc}}, \nu_{S_{Coll}}, \nu_{S_{GS}}, \nu_{L_{HS}}, \nu_{L_{Voc}}, \nu_{L_{Coll}}, \nu_{L_{GS}}, \nu_{Emp}, \nu_L)$,

and standard deviations of the ordered probit residuals are

$\boldsymbol{\Omega} = (\sigma_{\epsilon_W}, \sigma_{\epsilon_{L_{HS}}}, \sigma_{\epsilon_{L_{Voc}}}, \sigma_{\epsilon_{L_{Coll}}}, \sigma_{\epsilon_{L_{GS}}}, \sigma_{\epsilon_L})$.

Given the functional forms and the parameter vector definitions the likelihood function is:

$$L(\boldsymbol{\Theta},\boldsymbol{\Gamma},\boldsymbol{\Lambda},\boldsymbol{\Omega})=\prod_{i=1}^{N}\sum_{j=1}^{4}p_{\eta,j}\prod_{t=1}^{T}\prod_{a=1}^{5}\prod_{d=0}^{5}\prod_{g=0}^{5}\prod_{k=0}^{5}\prod_{q=0}^{5}\prod_{h=1}^{5}\left[\phi\left(\frac{\mu_{W,a}-\mathbf{X}_{it}\boldsymbol{\beta}_W-\eta_j}{\sigma_{\epsilon_W}}\right)\right.$$

$$\left.-\,\phi\left(\frac{\mu_{W,a-1}-\mathbf{X}_{it}\boldsymbol{\beta}_W-\eta_j}{\sigma_{\epsilon_W}}\right)\right]^{\mathbf{I}(\mu_{W,a-1}<l_{it}^{*}<\mu_{W,a})*Emp_{it}*(1-S_{HS,it}-S_{Voc,it}-S_{Coll,it}-S_{GS,it})}$$

$$\left[\Phi(\mathbf{Z}_{it}\boldsymbol{\beta}_{S_{HS}}+\nu_{S_{HS}}\eta_j)\right]^{S_{HS,it}*(1-HSGrad_{it})}\left[1-\Phi(\mathbf{Z}_{it}\boldsymbol{\beta}_{S_{HS}}+\nu_{S_{HS}}\eta_j)\right]^{(1-S_{HS,it})*(1-HSGrad_{it})}$$

$$\left[\Phi(\mathbf{Z}_{it}\boldsymbol{\beta}_{S_{Voc}}+\nu_{S_{Voc}}\eta_j)\right]^{S_{Voc,it}*HSGrad_{it}}\left[1-\Phi(\mathbf{Z}_{it}\boldsymbol{\beta}_{S_{Voc}}+\nu_{S_{Voc}}\eta_j)\right]^{(1-S_{Voc,it})*HSGrad_{it}}$$

$$\left[\Phi(\mathbf{Z}_{it}\boldsymbol{\beta}_{S_{Coll}}+\nu_{S_{Coll}}\eta_j)\right]^{S_{Coll,it}*HSGrad_{it}}\left[1-\Phi(\mathbf{Z}_{it}\boldsymbol{\beta}_{S_{Coll}}+\nu_{S_{Coll}}\eta_j)\right]^{(1-S_{Coll,it})*HSGrad_{it}}$$

$$\left[\Phi(\mathbf{Z}_{it}\boldsymbol{\beta}_{S_{GS}}+\nu_{S_{GS}}\eta_j)\right]^{S_{GS,it}*CollGrad_{it}}\left[1-\Phi(\mathbf{Z}_{it}\boldsymbol{\beta}_{S_{GS}}+\nu_{S_{GS}}\eta_j)\right]^{(1-S_{GS,it})*CollGrad_{it}}$$

$$\left[\Phi\left(\frac{\mu_{L_{HS},d}-\mathbf{Z}_{it}\boldsymbol{\beta}_{L_{HS}}-\nu_{L_{HS}}\eta_j}{\sigma_{\epsilon_{L_{HS}}}}\right)-\Phi\left(\frac{\mu_{L_{HS},d-1}-\mathbf{Z}_{it}\boldsymbol{\beta}_{L_{HS}}-\nu_{L_{HS}}\eta_j}{\sigma_{\epsilon_{L_{HS}}}}\right)\right]^{\mathbf{I}(\mu_{L_{HS},d-1}<l_{it}^{*}<\mu_{L_{HS},d})}$$

$$\left[\Phi\left(\frac{\mu_{L_{Voc},g}-\mathbf{Z}_{it}\boldsymbol{\beta}_{L_{Voc}}-\nu_{L_{Voc}}\eta_j}{\sigma_{\epsilon_{L_{Voc}}}}\right)-\Phi\left(\frac{\mu_{L_{Voc},g-1}-\mathbf{Z}_{it}\boldsymbol{\beta}_{L_{Voc}}-\nu_{L_{Voc}}\eta_j}{\sigma_{\epsilon_{L_{Voc}}}}\right)\right]^{\mathbf{I}(\mu_{L_{Voc},g-1}<l_{it}^{*}<\mu_{L_{Voc},g})}$$

$$\left[\Phi\left(\frac{\mu_{L_{Coll},k}-\mathbf{Z}_{it}\boldsymbol{\beta}_{L_{Coll}}-\nu_{L_{HS}}\eta_j}{\sigma_{\epsilon_{L_{Coll}}}}\right)-\Phi\left(\frac{\mu_{L_{Coll},k-1}-\mathbf{Z}_{it}\boldsymbol{\beta}_{L_{Coll}}-\nu_{L_{Coll}}\eta_j}{\sigma_{\epsilon_{L_{Coll}}}}\right)\right]^{\mathbf{I}(\mu_{L_{Coll},k-1}<l_{it}^{*}<\mu_{L_{Coll},k})}$$

$$\left[\Phi\left(\frac{\mu_{L_{GS},q}-\mathbf{Z}_{it}\boldsymbol{\beta}_{L_{GS}}-\nu_{L_{GS}}\eta_j}{\sigma_{\epsilon_{L_{GS}}}}\right)-\Phi\left(\frac{\mu_{L_{GS},q-1}-\mathbf{Z}_{it}\boldsymbol{\beta}_{L_{GS}}-\nu_{L_{GS}}\eta_j}{\sigma_{\epsilon_{L_{GS}}}}\right)\right]^{\mathbf{I}(\mu_{L_{GS},q-1}<l_{it}^{*}<\mu_{L_{GS},q})}$$

$$\left[\Phi(\mathbf{Z}_{it}\boldsymbol{\beta}_{Emp}+\nu_{Emp}\eta_j)\right]^{Emp_{it}}\left[1-\Phi(\mathbf{Z}_{it}\boldsymbol{\beta}_{Emp}+\nu_{Emp}\eta_j)\right]^{(1-Emp_{it})}$$

$$\left[\Phi\left(\frac{\mu_{L,h}-\mathbf{Z}_{it}\boldsymbol{\beta}_L-\nu_L\eta_j}{\sigma_{\epsilon_L}}\right)-\Phi\left(\frac{\mu_{L,h-1}-\mathbf{Z}_{it}\boldsymbol{\beta}_L-\nu_L\eta_j}{\sigma_{\epsilon_L}}\right)\right]^{\mathbf{I}(\mu_{L,h-1}<l_{it}^{*}<\mu_{L,h})}.$$

The likelihood function is changed when we examine the complementarity of school across differing student occupational types. Instead of conditioning the in-school labor demand equations on the schooling level we estimate labor demand equations for each student occupational type and include dummy variables for the level of schooling as covariates.

Identification

The endogenous variables in the model are school, employment, and hours of work demands and the cumulative history of these variables. Identification comes through three mechanisms: non-linearities in the model (probits, ordered probits, and the distributionof the discrete factor), restrictions on the covariance matrix for disturbances in the system equations, and exclusion restrictions. Given that the model is built with probit and ordered probit models, there are significant non-linearities in the model.

The factor model is identified through restrictions derived from the factor structure. The model assumes that correlation between the error terms in the schooling, work, and wage equations exists and the unobserved factor is the only source of correlation between the equations. Thus, assuming that the factor is the common source of correlation, the covariance between error terms is identified as a product of the factor loadings and the variance of the unobserved factor. This restriction allows the model to be identified.

The model also incorporates explicit and derived dynamic exclusion restrictions. Explicit exclusion restrictions include covariates that are in the current period schooling, employment, and labor demand equations but are not included in the wage equation. The set of exclusion restrictions includes parents' education, whether the individual was born to a teen mother, whether the individual was in a two-parent family at age 12, and the household income in the previous year. As exclusion restrictions these variables are included in the underlying schooling and labor demand equations but are excluded from the wage equation. The variables are included as exclusion restrictions because they are known to the individuals, affect schooling and labor demand, but are not observed by employers making the wage offers—the employer does not have access to this information when making wage offers.

In addition to explicit exclusion restrictions, the model derives dynamic exclusion restrictions. By modeling the schooling and work decisions in previous periods, the stock of schooling, labor, and in-school work are dependent on the covariates from the previous time periods, while wages are dependent upon covariates in the current period. Even the stocks of school, labor, and in-school work in prior periods are valid dynamic exclusion restrictions, as they only affect future wages through their effect on current flows of school and work which determine the current period's stock.

Data

Data are from the 1997-2008 rounds of the National Longitudinal Study of Youth 1997 (NLSY97). The NLSY97 is comprised of a nationally representative sample of 6,748 youths plus an oversample of 2,236 Hispanic or Latino and black youths, aged 12-16 years in 1997. The NLSY97, administered annually, collects data on youths' education, employment, and background characteristics.

The NLSY97 data contain weekly employment status and usual work hours for any jobs held by individuals 14 years or older. From this information, we use high school, college, and graduate school enrollment and graduation indicators along with in-school and out-of-school labor force participation and hours or work variables to estimate the schooling and work selection equations. Furthermore, we have information on hourly rate of pay for the respondent's jobs.

We define the academic year as the a 26 week period covering 40^{th}-48^{th} weeks of a year and the 6^{th} -22^{nd} weeks of the subsequent year.[29] This period should capture most full weeks in October, November, February, March, April, and May and exclude any weeks where students are on holiday or summer breaks. The academic year as defined should be an accurate measure and provide consistent indicators of in-school employment. An individual was deemed to work while in school if she was employed during any week of the 26 week period.

As the theoretical model outlines, the sum-of-labor and sum-of-in-school-employment variables were constructed by accumulating total work hours in all previous years. Therefore, the person-year observations keep a running total of total hours worked and hours worked in school. Also form the theoretical model, the Taylor series expansion derived the measure (t-1); this corresponds to the individual's age which is included as a covariate. Additional covariates in the model's vector **X** include indicator variables for sex, race, nationality (U.S. born), and marital status of the individual along with the AFQT percentile score, the local unemployment rate, and a set of inverse-distance weighted prices to goods in ACCRA markets—reflecting differences in the prices of energy, housing, clothing, food, and entertainment goods that will affect both demand for school and labor as well as local area wage differentials.[30] In addition to the variables in **X**, the vector of covariates for the school and labor demand equations, **Z**, includes exclusion restrictions: indicator variables for whether the mother and father were high school or college

[29] This measure of the academic year mimics the academic year created by Ruhm (1997) and Light (1999).

[30] The included prices are average ACCRA market costs for monthly energy (natural gas, fuel oil, electricity, and any other forms) expenditures, a 2400 sq.ft. new urban-area house with all utilities, a man's dress shirt, one pound of ground beef, half-gallon of whole milk, and an evening movie theater ticket. A description of the created inverse-distance weighted prices is available from the authors upon request.

graduates, if the individual was born to a teen mother, whether the individual was in a two-parent family at age 12, and a continuous variable for the household income in the previous year.

For the extended analysis of in-school employment by occupational type, we consider reports regarding the occupation of the main job held while the student was enrolled in school. The original 3-digit occupation codes were reclassified, using the procedures detailed in Appendix B, to distinguish between “blue-collar,” “white-collar” and “service” occupations. These broad occupational designations do not provide information regarding the occupations relative alignment with educational activities, but align closely to the blue- and white-collar distinction made by Keane and Wolpin (1997) in their analysis of young men’s careers. The broad occupational groupings also provide aggregation of occupations with more similar characteristics yet limit unimportant year-to-year changes in occupations due to minor changes in job duties or spurious coding differences.

The young ages of children in the NLSY97 alleviate concerns of correcting for initial conditions bias for work and schooling decisions. First, employment history information was retrospectively collected back to age 14, the youngest eligible working age set by the Fair Labor Standards Act. Second, to avoid an initial conditions bias, we drop individuals from the dataset who were older than 16 at the 1997 survey date (n = 692). Since employment history information was collected back to the start of 1994 and the minimum age across states to leave school is age 16, the restrictions sufficiently capture the initial conditions of both work and schooling for the subjects. Due to the division of in-school employment into high school, college, and graduate school employment, we drop person-year observations where the individual has not yet completed the 8th grade. This restriction drops all observations for 321 subjects and a total of 5,717 person-years.

We resolved inconsistencies in the regarding marital status variables, educational degree indicators, and grade completion information. For person-years when marital status was missing, observations with consistent marital status in lag and lead years were set to the same value as the lag and lead years, and observations in the final year of the survey data were set the lag value of marital status, remaining observations below age 18 were defined as “single”. For person-years that do not include a degree attainment indicator, we replaced all degree indicators to a value of zero if the person was enrolled in high school. Finally, we replace the highest grade completed to 12 years if a high school degree was indicated but the highest completed grade reported was less than 12 years and the lead value of the completion grade is at least 12 years.

Other data restrictions include dropping observations missing county of residence (587 person-years) and correcting for missing information on AFQT percentile scores and parental information. Individuals missing an AFQT percentile score had this value set to the mean score and an indicator variable for the missing score is included in analyses. Furthermore, if information on the subject’s mother’s teen age at birth, two parents present in the household at age 12, maternal education, or paternal education was missing, the corresponding indicator variables were set to zero and an additional indicator variable for missing information was created. Finally, since the end result is to estimate the effects of in-school employment on future human capital (wages) we drop individuals from the data who do not contribute to the wage equation at an age of at least 22 years (n = 771).[31]

[31] In order to avoid missing work history information, all data restrictions were made after the construction of work history measures. This provides valuable information given that the NLSY97 collects retrospective histories if an interview is missed.

Descriptive Statistics of Data

Table 3.1 provides unweighted descriptive statistics for individuals in the final sample. The sample includes 75,719 person-year observations from 7,253 youths. The sample is well balanced by sex and the low proportion of non-Hispanic white respondents, relative to the US population, reflects the oversample of Hispanic or Latino and black youths. Almost 90% of respondents complete high school; although, this proportion is slightly inflated due to deleting individuals who never reported completing the 8^{th} grade. Adequate observations are available for estimating the schooling, work, and wage equations. The average oldest age at which we observe the youths is 25.7 years. This age is sufficient to observe first post-schooling jobs for many individuals.

Table 3.2 displays average in-school work experience for the sample. The first column of means describes work behavior over all schooling levels whereas columns (2)-(5) segment the employment behavior by schooling levels. A high proportion of individuals, 0.88, work while attending school at some point. This proportion is lower for working in high school, 0.77, but over 0.9 for two-year, four-year, and graduate school students. Almost two thirds of individuals are employed while in school during any given school year, 65%. Again, participation is higher for post-secondary students. The highest participation rate is for two-year college students, 87% work in a given year. The high participation rates across all schooling levels provide suggestive evidence that in-school work is not highly counter-productive to human capital investment, as it is not avoided for any schooling level.

In-school workers are also employed for a high proportion of the school year on average. The number of weeks student workers are employed, over the 26-week year ranges from 17 weeks for high school workers to 21 weeks for two-year college students. These student workers

Table 3.1: Descriptive Statistics	
Male	0.504
	(0.006)
White	0.491
	(0.006)
Black	0.262
	(0.005)
Hispanic	0.211
	(0.005)
Other race	0.037
	(0.002)
Foreign born	0.063
	(0.003)
Highest degree observed	
No degree	0.106
	(0.003)
HS degree	0.594
	(0.006)
AA degree	0.066
	(0.003)
Bachelor's degree	0.208
	(0.005)
Graduate degree	0.026
	(0.002)
Oldest age observed	25.7
	(0.016)
n =	7,253
person-years =	75,719
person-years for HS enrollment =	22,788
person-years for College enrollment =	40,861
person-years for Graduate School enrollment =	5,209
person-years for HS work equation =	19,499
person-years for College work equation =	10,454
person-years for Grad School work equation =	769
person-years for non-school work equation =	41,551
person-years for wage equation =	36,379

Note: the sample includes youths aged 12-29 years in the NLSY97. Clustered standard errors are in parentheses.

Table 3.2: Description of in-school work experience

	(1)	(2)	(3)	(4)	(5)
	All School Levels	**High School**	**2-year College**	**4-year College**	**Graduate School**
Ever employed during school	0.879	0.773	0.920	0.923	0.908
	(0.004)	(0.005)	(0.006)	(0.005)	(0.014)
Employed during school year	0.652	0.526	0.870	0.818	0.823
	(0.004)	(0.004)	(0.007)	(0.006)	(0.017)
School weeks employed (of 26)	12.25	9.14	18.38	16.09	15.40
	(0.090)	(0.095)	(0.202)	(0.171)	(0.485)
School weeks employed (of 26)	18.79	17.36	21.13	19.67	18.72
if employed ≥ 1 week	(0.074)	(0.097)	(0.138)	(0.130)	(0.382)
Hours worked per week	12.31	7.97	22.92	16.69	20.37
	(0.115)	(0.098)	(0.330)	(0.248)	(0.889)
Hours worked per week	18.88	15.14	26.35	20.41	24.75
if employed ≥ 1 week	(0.131)	(0.134)	(0.294)	(0.247)	(0.872)
Total in-school work hours	1623	697	1,273	1,208	909
	(19.26)	(8.87)	(26.52)	(21.98)	(49.53)
Total in-school work hours	1854	862	1,447	1,384	1231
if ever employed	(20.36)	(9.70)	(27.67)	(23.00)	(56.41)
White-collar in-school work	0.523	0.417	0.561	0.620	0.879
	(0.004)	(0.005)	(0.008)	(0.006)	(0.013)
Blue-collar in-school work	0.1635	0.199	0.164	0.129	0.038
	(0.003)	(0.004)	(0.006)	(0.004)	(0.008)
Service in-school work	0.313	0.383	0.273	0.250	0.083
	(0.003)	(0.005)	(0.007)	(0.006)	(0.011)

Note: the sample includes 7,253 youths aged 12-29 years over the 1997-2008 surveys in the NLSY97. Clustered standard errors are in parentheses.

also amass a significant number of work hours in school. On average, the 88% of students who work at some point in school gain 1,854 hours of work experience over their academic career, the rough equivalent to one year of full-time work experience.

There are clear trends in the types of jobs that student workers hold at different levels of education. White-collar jobs are the most common job type at any schooling level. Though, the proportion of in-school workers holding white-collar jobs increases at each progressively higher level of education, as the proportion of both blue-collar and service workers declines. The proportion of in-school work conducted in white-collar occupations moves from 0.417 for high school students to 0.88 for graduate school students. This upward trend in white-collar student jobs sees a large jump at the graduate school level. This result may stem entirely from an increase in the opportunities available to graduate students but may reflect selection into more complementary occupations.

Of the student workers who are not in white-collar jobs, roughly twice as many in-school workers hold service jobs as blue-collar jobs. The one exception is for in-school workers enrolled in two-year colleges, where the ratio of service to blue-collar workers is lower at roughly 1.5. Again, these trends may reflect opportunity or selection into complementary work types.

Multivariate Results

We present estimates from OLS wage equation estimates that do not correct for endogeneity and wage equation estimates from the simultaneous-equation DFM. OLS is useful starting point for two reasons. First, log-linear wage equations are commonly studied and provide a familiar setting to examine the point estimates of the model. Second, because we are the first study to whether school and work are complements in the production of human capital and are correcting for endogeneity, OLS is a reference from which we can determine how endogeneity affects the point estimates for this effect. For both OLS and DFM estimates we present three models. The first model treats all schooling and work experience the same. Thus, as outlined in equation (6) there is one measure of the stock of in-school work experience. The second and third models are exploratory extensions to this model that separate the in-school work experience by schooling level and student job type, respectively.

For the extended models, the coefficients measuring the complement/substitute measure of school and work include a base measurement—for the base level of school (high school) or type of work (white-collar)—and differences in the complementarity effect from the base case—for the additional schooling levels and occupation types. The corresponding complement/substitute measures for alternative types of school or work can be determined by adding the coefficient on the base schooling or work type with the coefficient for the alternative measure. Thus the estimate of interest, determining complement or substitute, for types of school or work that are not the base case is the sum of the two coefficients. We report both the original coefficients and the linear combinations and their respective standard errors for all types of school and occupations.

Table 3.3 shows OLS estimates of the wage equation. The first column presents results from OLS estimation of equation (6). The estimate states that work and school are substitutes in the production of human capital, indicated by the negative coefficient and is statistically different from zero at the 10% level of significance. This result suggests that working while enrolled in school reduces the human capital production of each input.

Table 3.3: Non-instrumented, single ln(wage) equation estimates

Labor	0.0269***	0.0277***	0.0279***
	(0.0022)	(0.0022)	(0.0022)
Σ(Labor^2)	-0.0013***	-0.0013***	-0.0015***
	(0.0005)	(0.0005)	(0.0005)
Years of Education	0.0526***	0.0498***	0.0514***
	(0.0031)	(0.0033)	(0.0031)
In-school Work Coefficients			
Base Work	-0.0092*	-0.0184***	0.0141**
	(0.0049)	(0.0068)	(0.0078)
2 Yr College Work		0.0088	
		(0.0096)	
4 Yr College Work		0.0219**	
		(0.0110)	
Grad Work		0.1064***	
		(0.0303)	
Blue-collar Work			-0.0212**
			(0.0096)
Service Work			-0.0702***
			(0.0081)
Calculated Associations by Type of School and Work			
High School		-0.0184***	
		(0.0068)	
2 Yr Coll work		-0.0096	
		(0.0077)	
4 Yr Coll work		0.0035	
		(0.0088)	
Grad Work		0.0880***	
		(0.0297)	
White-collar			0.0141**
			(0.0078)
Blue-collar			-0.0071
			(0.0089)
Service			-0.0561***
			(0.0074)

Note: The table displays coefficients (top panel) and linear combinations of coefficients (bottom panel) from OLS wage equations. The sign of coefficients for in-school work experience determines if the school work imputs are direct complements (positive) or substitutes (negative). The sample includes 7,253 youths aged 12-29 years over the 1997-2008 surveys in the NLSY97. Robust clustered standard errors are in parentheses.

The second column presents OLS estimates when in-school work is disaggregated by schooling level. The linear combinations of coefficients are presented in the bottom panel of Table 3.3. The OLS results show that working and high school education are direct substitutes in the production of human capital. However, work and graduate school are compliments in the production of human capital. The sign of the sum of the interactions of two- and four-year college indicate that work is a substitute to two-year college education and complement to four-year schooling although the estimates are not statistically different from zero at the 10% level of significance. The third column, estimating the effects of in-school work in differing types of employment, suggests that schooling and white-collar jobs are complements in the production of human capital while blue-collar (not statistically significant) and service occupations are substitutes.

Table 3.4 presents the dynamic DFM results of the three specifications. After controlling for endogeneity, the results differ considerably. The first column of Table 3.4 shows that after controlling for endogeneity work and school are, on average, complementary in the production of human capital. Correcting for endogeneity therefore changes the inference from school and work are substitutes to school and work are complements in producing human capital.

The estimates in the second column of Table 3.4 reinforce that employment is a substitute for high school and a complement to graduate school in human capital production. The DFM results, however, show that employment is also complementary with two-year college education and a substitute to four-year college. Not only is work a complement to two-year college

Table 3.4: DFM ln(Wage) Equations, One Time-Consistent Error			
Labor	0.0186***	0.0151***	0.0182***
	(0.0008)	(0.0009)	(0.0009)
Σ(Labor^2)	-0.0014***	-0.0008***	-0.0014***
	(0.0002)	(0.0002)	(0.0002)
Years of Education	0.0262***	0.0247***	0.0279***
	(0.0013)	(0.0014)	(0.0013)
In-school Work Coefficients			
Base Work	0.0054***	-0.0389***	-0.0132***
	(0.0013)	(0.0035)	(0.0022)
2 Yr College Work		0.1399***	
		(0.0046)	
4 Yr College Work		-0.0266***	
		(0.0046)	
Grad Work		0.0892	
		(0.0152)	
Blue-collar Work			0.0493***
			(0.0038)
Service Work			0.0348***
			(0.0013)
Calculated Associations by Type of School or Work			
High School		-0.0389***	
		(0.0035)	
2 Yr Coll work		0.1010***	
		(0.0076)	
4 Yr Coll work		-0.0655***	
		(0.0075)	
Grad Work		0.0503***	
		(0.0163)	
White-collar			-0.0132***
			(0.0022)
Blue-collar			0.0361***
			(0.0052)
Service			0.0216***
			(0.0049)

Note: The table displays coefficients (top panel) and linear combinations of coefficients (bottom panel) from the wage equation in a dynamic simultaneous school enrollment, labor demand, wage equation model. Endogeneity is addressed using the Discrete Factor Method. The sign of coefficients for in-school work experience determines if the school work imputs are direct complements (positive) or substitutes (negative). The sample includes 7,253 youths aged 12-29 years over the 1997-2008 surveys in the NLSY97. Robust clustered standard errors are in parentheses.

enrollment, the degree of complementarity (magnitude) is greater than for graduate school workers.[32]

The high degree of complementarity between two-year college and work may reflect the type of studies and work undertaken at two-year colleges. Since the late 1970's greater than 60% of awarded Associate's Degrees were for an occupational curriculum (Cohen and Brawer, 2003, p.232). Thus, complementarity between two-year education and work may well be the result of the program of study for the average student being of a vocational nature and, therefore, more likely to complement student employment. Similarly, the findings that high school and four-year college attendance is a substitute for employment may stem from a greater focus on a liberal arts education for these students, a curriculum that does not complement current employment. Although many high school students take occupational courses, high school students most commonly study business and computer technology coursework (Levesque et al, 2008) and jobs relating to these occupations are rarely filled by high school students.

The third column of results in Table 3.4 shows that controlling for endogeneity flips the estimated productivity effect of undertaking work and school at the same time for all student occupational types relative to the OLS estimates. The DFM shows that white-collar occupations are a substitute to school in human capital production while blue-collar and service jobs are complements to schooling. It is interesting that white-collar occupations are a substitute to school yet work is estimated to be complementary to graduate studies, in which a high proportion of graduate student workers are in white-collar occupations. This anomaly is likely driven by a differential effect across white-collar jobs. Two-thirds of graduate school students work in Professional or Technical occupations while in school and we hypothesize that these jobs are

[32] As shown in equation (4), although the direct cross partial derivative is not obtained from the wage equation estimates the sign *and* relative magnitude of complementarity is maintained.

more closely related to the students' studies.[33] Alternatively, 10% of students in high school, two-year college, or four-year college in our NLSY sample report occupations that are in Professional or Technical occupations.[34]

Likelihood ratio tests comparing the alternative specifications, columns (2) and (3), to the base model reject the null model in favor of the alternative specifications. As such, the results confirm that indeed certain types of school and work are complementary in producing human capital, while other combinations of work and schooling types decrease the productivity of each. A more detailed analysis would be beneficial. However, examination of interactions among all schooling levels *and* occupational types can overwhelm our model.

Identification and Auxiliary Equations

Because the auxiliary school and labor demand equations are reduced form the coefficient estimates have no interpretable meaning they are relegated to Appendix C. These equations do, however, control of the correlation of individual characteristics and, importantly, the exclusion restrictions with school and labor demand. Therefore, tests of the joint significance of the set of exclusion restrictions under the assumption of independent errors provide preliminary evidence on their usefulness as instruments. We ran the school enrollment probit equations and non-enrolled employment probit equation in Stata. The exclusion restrictions (parents' education, born to a teen mother, two-parent family at age 12, and previous household income) were jointly significant at the 0.0001 level of significance in all equations. To estimate

[33] Seven of the ten most common occupations for graduate student workers are in teaching or counseling occupations.
[34] Professional or Technical occupations are defined as three digit occupation codes in the Managerial and Professional Specialty Occupation (003-037), Professional Specialty Occupation (043-199), and Technical Occupation (203-235) groupings for the 1990 Census Occupation Codes.

the ordered single-index school work equations and the non-enrolled hours of work equations we ran interval regression models in Stata with the intervals defined as they were in the DFM ordered probits. With one exception, the exclusion restrictions are again significant at the 0.0001 level of significance. The p-value for joint significance of the exclusion restrictions in the graduate school employment equation is $p = 0.0129$. These results suggest that the exclusion restrictions are sufficiently strong in identifying school and work decisions.

Additionally, we ran preliminary tests on our exclusion restrictions in an instrumental variables (IV) version of our wage equation. Identification in IV rest on the assumptions that the exclusion restrictions significantly predict the endogenous variables (i.e. are strong) and are validly omitted from the wage equation (i.e. are valid). The endogenous variables are identified as the stocks of labor, in-school experience, and education. In-school experience is not defined by school level or occupation; this restriction allows us to test for weak instruments using the Kleibergen-Paap statistic provided by Stata according to the critical values of the Cragg-Donald statistic defined for three endogenous variables by Stock and Yogo (2005).

The first IV model we run includes the the family and individual background variables as exclusion restrictions. The Kleibergen-Paap statistic is 14.47; suggesting TSLS relative bias of less than 10%, where relative bias is the ratio of the expected bias in the TSLS estimation to the bias in OLS estimation. This result augments the joint significance of exclusion restrictions in the auxiliary demand equations to further suggest that we do not have a problem with weak instruments. Based on the Hansen J statistic the IV model fails to reject the null hypothesis that all instruments are valid (p-value = 0.1858). This result implies that there is not a problem of validity in the exclusion restrictions for our model.

The DFM is technically identified through non-linearities in the model (Mroz, 1999) and naturally derived exclusion restrictions from the dynamic nature of the model. We test this form of identification by including the exclusion restrictions in the wage equation and re-estimate the base model. Table 3.5 displays the original DFM estimates from the three models (columns 1, 3, and 5) along with models that include the exclusion restrictions in the wage equation. The results show that the estimates do significantly change when the exclusion restrictions are added to the model. This suggests that the dynamic DFM model is indeed identified without explicit exclusions restrictions and should be investigated as a potential solution for similar research.

Conclusion

We use longitudinal data, from the NLSY97, to show how in-school employment affects the flow of human capital by identifying if school and work are complements or substitutes in the production of human capital. A theoretical and accompanying empirical model, developed from Bray (2005), allows us to estimate the sign of the cross-partial derivatives for schooling and labor in the human capital production function to indicate how undertaking these activities together—working while enrolled in school—affects the productivity of each input. Endogeneity is addressed by jointly modeling the schooling and labor choices of individuals along with their wages and using the Discrete Factor Method to control for unobserved heterogeneity that is common among the system. Our research has several important implications for the study of in-school employment and human capital development.

First, the effects of work and school as inputs into human capital production are indeed affected by undertaking the two activities at the same time. Overall, work and school are

Table 3.5: Sensitivity Tests

	(1)	(2)	(3)	(4)	(5)	(6)
Exclusion Restrictions in Wage Equation	**No**	**Yes**	**No**	**Yes**	**No**	**Yes**
Labor	0.0186***	0.0176***	0.0151***	0.0144***	0.0182***	0.0171***
	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Σ(Labor^2)	-0.0014***	-0.0014***	-0.0008***	-0.0007***	-0.0014***	-0.0013***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Years of Education	0.0262***	0.0227***	0.0247***	0.0197***	0.0279***	0.0237***
	(0.0013)	(0.0013)	(0.0014)	(0.0014)	(0.0013)	(0.0013)
Calculated Associations by Type of School or Work						
In-school work	0.0054***	0.0055***				
	(0.0013)	(0.0018)				
High School			-0.0389***	-0.0344***		
			(0.0035)	(0.0035)		
2 Yr Coll work			0.1010***	0.0984***		
			(0.0076)	(0.0076)		
4 Yr Coll work			-0.0655***	-0.0650***		
			(0.0075)	(0.0076)		
Grad Work			0.0503***	0.0533***		
			(0.0163)	(0.0162)		
White-collar					-0.0132***	-0.0125***
					(0.0022)	(0.0022)
Blue-collar					0.0361***	0.0372***
					(0.0052)	(0.0050)
Service					0.0216***	0.0180***
					(0.0049)	(0.0048)

Note: The table displays coefficients (top panel) and linear combinations of coefficients (bottom panel) from the wage equation in a dynamic simultaneous school enrollment, labor demand, wage equation model. Endogeneity is addressed using the Discrete Factor Method. The sign of coefficients for in-school work experience determines if the school work inputs are direct complements (positive) or substitutes (negative). The sample includes 7,253 youths aged 12-29 years over the 1997-2008 surveys in the NLSY97. Robust clustered standard errors are in parentheses.

complementary in producing human capital. This finding suggests that the timing of inputs into human capital production can alter the productive efficiency of those inputs.

Second, the magnitude, and even direction, of a complementary effect is sensitive to the type of schooling and work that is undertaken. Working while in high school or four-year college and holding a white-collar occupation while in school reduce the productivity of these human capital inputs relative to undertaking them as separate times. Conversely, students who work while enrolled in a two-year or graduate degree program or hold a blue- or service job in school increase the productive efficiency of each input. A closer examination of the interaction between differing school curriculum *and* student occupation is beyond the scope of this essay but should be undertaken further illuminate combinations of work and studies that should be considered to improve human capital development for students.

Finally, the dramatic differences in the results between models that do and do not control for the endogeneity of school and work illustrate its importance in estimation. Not only do the relative magnitudes of estimated effects change, but the qualitative implication—whether the inputs are complements or substitutes—commonly changes after controlling for endogeneity. Investigation of our set of exclusion restrictions suggests that they are both strong and valid. However, sensitivity tests demonstrate that identification of the DFM on non-linearities and the dynamic nature of the model provides similar results and may be adequate for future work.

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APPENDIX A

OCCUPATIONAL CLASSIFICATIONS

The PSID provided 3-digit 1970 Census group definitions for the 1984 through 2001 waves and 3-digit 2000 Census group definitions for the 2003 and later surveys. To make this information uniform for all survey rounds, we recoded the occupation codes to 1990 Census definitions for all years using the crosswalk provided by IPUMS-USA (http://usa.ipums.org/usa/volii/documents/occ1990_xwalk.xls). The occupations were subsequently defined as “blue-collar,” “white-collar,” or “service” following listings provided by the Bureau of Labor Statistics (Chao and Utgoff, 2003). Twenty-six occupations were not included in the BLS list; we have categorized these occupations within the classification that is subjectively appropriate. A list of the classifications appears in Table A-1. In addition to the occupational classifications, we also include a fourth category for people who were not employed at the time of the survey.

There are two notes of interest in constructing these categorical variables. First, the PSID identifies individuals serving in the armed forces but does not indicate their occupation while in military service. Since there were too few observations to classify military service as a separate occupation, we dropped person-year observations for individuals serving in the armed forces during the 5-year occupational history window. Second, a small number individuals report being unemployed or out of the labor force but still indicate an occupation. For consistency, we coded these individuals as not-employed.

Our main occupation variables represent average values for over the five years *t*-4, *t*-3, *t*-2, *t*-1, and *t*. In the years up to 1997, we used information on the occupation of the primary job at the time of the interview for all of these periods. In years after 1997, when the PSID interviewed biennially, we used available retrospective work history information to identify the occupation of individuals in the month one year prior to the survey month to obtain the measures for periods *t*-3 and *t*-1. For instance, an individual's 1998 occupation is defined as that reported in the month one year prior to the 1999 interview.[35] If data were missing for any years between t-4 and t (after including the constructed values just discussed), averaging took place over the period for which the data were available.

We merged onto the dataset information on the physical demands of occupations using data from the Dictionary of Occupational Titles (DOT): Revised Fourth Edition (1991), which provides a five point ordinal measure of the physical demands for 12,742 occupations. The demands are listed as Sedentary, Light Work, Medium Work, Heavy Work, and Very Heavy Work (see http://www.occupationalinfo.org/appendxc_1.html#STRENGTH).

We matched the physical demand characteristics of DOT occupations to the Census occupational codes by coding the five measures to integers, one to five, increasing in physical demands. The DOT occupations and physical demand scores were then matched to Occupational Employment Statistics (OES) codes provided by the Bureau of Labor Statistics (BLS Crosswalk Center) and averaged over the DOT occupations within each OES occupation. Finally, physical demands by OES occupation were weighted according to 1997 estimates of the number of individuals employed in each of the OES occupations (BLS, 2010) and matched to the 1990 Census occupation codes for person-years in our PSID data set.

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[35] The retrospective information in the non-interview years (1998, 2000, 2002, 2004, and 2006) provides fewer occupational transitions than interview years. A lower proportion of transitions during the recalled employment history is consistent with seam effects, which have been found in the employment history of the PSID. However, occupational measures during the non-interview years match the characteristics of those during interview years in the terms of the number of observations and proportion of individuals in each occupational state (Callegaro, 2007).

Table A-1. Classification of occupations

White-collar

Professional Specialty & Technical Occupations (043-235), *n* = 5850
Executive, Administrative, & Managerial Occupations (003-37), *n* = 6975
Sales Occupations (243-85), *n* = 2334
Administrative Support Occupations (303-48, 353, 356-89), *n* = 1767
Classified by the Authors
  Other Telecom Operators (349), *n* = 1
  Postal Clerks, Excluding Mail Carriers (354), *n* = 138
  Managers, Farms, Except Horticultural (475), *n* = 109

Blue-collar

Precisions Production, Craft, & Repair Occupations (503-29, 534-47, 553-654, 656-58, 666-69, 675-99), *n* = 6451
Machine Operators, Assemblers, & Inspectors (703-14, 723-24, 726-29, 734-36, 738-48, 753-77, 783-800), *n* = 1927
Transportation and Material Moving Occupations (803-59), *n* = 3059
Handlers, Equipment Cleaners, Helpers, and Laborers (483-87, 489, 864-89), *n* = 1870
Classified by the Authors
  Farmers, Except Horticulture (473), *n* = 420
  Farm Workers (477,479), *n* = 310
  Graders and Sorters, Agricultural Products (488), *n* = 4
  Miscellaneous Electrical and Electronic Equipment Repairers (533), *n* = 4
  Not Specified Mechanics and Repairers (549), *n* = 317
  Miscellaneous Woodworking Machine Operators (733), *n* = 5
  Miscellaneous Textile Machine Operators (749), *n* = 63
  Machine operators, not specified (779), *n* = 869

Service Jobs

Protective, Food, Health, Cleaning, and Personal Service (413-69), *n* = 2438
Classified by the Authors
  Mail Carriers, Postal Service (355), *n* = 164
  Housekeepers and Butlers (405), *n* = 141
  Private Household Cleaners and Servants (407), *n* = 8

NOTE: Groups are based on 1990 3-digit Census occupation codes in parentheses. Blue-collar, white-collar, and service job classifications are based on the work of Chao and Utgoff (2003) except for occupations “Classified by the Authors,” which were classified for use in this paper only. The numbers of observations, *n*, refer to person-year observations between 1984 and 2005.

APPENDIX B

OCCUPATIONAL CLASSIFICATIONS

The NLSY provided 3-digit 2000 Census group definitions for jobs in each survey round. The occupations were subsequently defined as “blue-collar,” “white-collar,” or “service” following listings provided by the Bureau of Labor Statistics (Chao and Utgoff, 2003). In order to make occupations relate to the BLS definitions we recoded the occupation codes to 1990 Census definitions for all years using the crosswalk provided by IPUMS-USA (http://usa.ipums.org/usa/volii/documents/occ1990_xwalk.xls). Twenty-six occupations were not included in the BLS list; we have categorized these occupations within the classification that is subjectively appropriate. A list of the classifications appears in Table A-1.

APPENDIX C

COEFFICIENT ESTIMATES FROM SIMULTANEOUS EQUATION DFM MODELS

HS Enrollment Probit

Constant	8.6684	Constant	8.6508	Constant	8.2627
	(0.3952)		(0.3953)		(0.3994)
labor t-1	-0.1127	labor t-1	-0.1128	labor t-1	-0.1165
	(0.0122)		(0.0118)		(0.0113)
sum(HS*l)	0.1372	sum(HS*l)	0.1182	sumwhite	0.2463
	(0.0296)		(0.0295)		(0.0493)
				sumblue	0.1511
					(0.0519)
				sumserve	0.1452
					(0.0363)
years of school	0.4825	years of school	0.4824	years of school	0.4778
	(0.0126)		(0.0126)		(0.0126)
home cost	-0.0024	home cost	-0.0024	home cost	-0.0027
	(0.0003)		(0.0003)		(0.0003)
energy costs	0.3815	energy costs	0.3768	energy costs	0.4015
	(0.1527)		(0.1527)		(0.1520)
dress shirt	0.0150	dress shirt	0.0147	dress shirt	0.0153
	(0.0047)		(0.0047)		(0.0047)
price ground beef	0.6135	price ground beef	0.6074	price ground beef	0.7289
	(0.1235)		(0.1236)		(0.1243)
price milk	0.1943	price milk	0.1876	price milk	0.2196
	(0.1452)		(0.1453)		(0.1461)
mother < HS degree	-0.0786	mother < HS degree	-0.0774	mother < HS degree	-0.0813
	(0.0274)		(0.0274)		(0.0275)
mother >= Coll degree	0.0824	mother >= Coll degree	0.0809	mother >= Coll degree	0.0838
	(0.0465)		(0.0466)		(0.0467)
mother educ missing	-0.0940	mother educ missing	-0.0945	mother educ missing	-0.0953
	(0.0468)		(0.0467)		(0.0468)
father < HS degree	-0.1207	father < HS degree	-0.1194	father < HS degree	-0.1193
	(0.0302)		(0.0302)		(0.0302)
father >= Coll degree	0.1040	father >= Coll degree	0.1044	father >= Coll degree	0.1038
	(0.0466)		(0.0467)		(0.0468)

father educ missing	-0.1508	father educ missing	-0.1505	father educ missing	-0.1509
	(0.0307)		(0.0307)		(0.0308)
HH income	2.1661	HH income	2.0888	HH income	2.2356
	(0.8047)		(0.8051)		(0.8073)
HH incomesq	0.0000	HH incomesq	0.0000	HH incomesq	0.0000
	(0.0000)		(0.0000)		(0.0000)
HH income missing	1.0563	HH income missing	1.0568	HH income missing	1.0648
	(0.0292)		(0.0293)		(0.0293)
local UR	0.0046	local UR	0.0046	local UR	0.0046
	(0.0006)		(0.0006)		(0.0006)
teen mother	-0.0089	teen mother	-0.0079	teen mother	-0.0095
	(0.0320)		(0.0320)		(0.0320)
teen mother (missing)	0.1369	teen mother (missing)	0.1406	teen mother (missing)	0.1388
	(0.0423)		(0.0423)		(0.0424)
two parents age 12	0.1888	two parents age 12	0.1848	two parents age 12	0.1905
	(0.0276)		(0.0276)		(0.0276)
two parents age 12 (miss)	-0.0381	two parents age 12 (miss)	-0.0388	two parents age 12 (miss)	-0.0407
	(0.0345)		(0.0345)		(0.0345)
age	-0.6569	age	-0.6553	age	-0.6477
	(0.0115)		(0.0115)		(0.0116)
male	-0.0366	male	-0.0383	male	-0.0332
	(0.0230)		(0.0230)		(0.0235)
black race	0.1900	black race	0.1896	black race	0.1864
	(0.0304)		(0.0305)		(0.0306)
hispanic	0.0278	hispanic	0.0250	hispanic	0.0289
	(0.0323)		(0.0322)		(0.0323)
other race	0.0047	other race	0.0017	other race	0.0074
	(0.0673)		(0.0679)		(0.0670)
foreign	0.0356	foreign	0.0375	foreign	0.0322
	(0.0453)		(0.0452)		(0.0453)
AFQT percentile	0.0037	AFQT percentile	0.0038	AFQT percentile	0.0036
	(0.0006)		(0.0006)		(0.0006)
AFQT missing	-0.1173	AFQT missing	-0.1184	AFQT missing	-0.1160
	(0.0291)		(0.0292)		(0.0291)
married	-0.5566	married	-0.5576	married	-0.5655
	(0.0928)		(0.0930)		(0.0934)

Two-year Collge Enrollment Probit

Constant	-0.9404	Constant	-0.5718	Constant	-0.3628
	(0.2554)		(0.2566)		(0.2475)
labor t-1	-0.0032	labor t-1	-0.0062	labor t-1	-0.0035
	(0.0036)		(0.0036)		(0.0036)
sum(s*l)	0.1294	sum(HS*l)	0.1586	sumwhite	0.2242
	(0.0109)		(0.0160)		(0.0119)
		sum(2yr*l)	0.2579	sumblue	0.0753
			(0.0160)		(0.0196)
		sum(4yr*l)	-0.2975	sumserve	0.0281
			(0.0235)		(0.0146)
years of school	0.1957	years of school	0.2303	years of school	0.1689
	(0.0105)		(0.0111)		(0.0102)
home cost	0.0001	home cost	0.0001	home cost	-0.0004
	(0.0002)		(0.0002)		(0.0002)
energy costs	-0.0295	energy costs	-0.0018	energy costs	0.0421
	(0.0963)		(0.0969)		(0.1016)
dress shirt	0.0121	dress shirt	0.0098	dress shirt	0.0145
	(0.0051)		(0.0051)		(0.0050)
price ground beef	-0.3494	price ground beef	-0.3592	price ground beef	-0.2448
	(0.0671)		(0.0679)		(0.0679)
price milk	0.4889	price milk	0.4490	price milk	0.1726
	(0.0912)		(0.0920)		(0.0974)
mother < HS degree	-0.0644	mother < HS degree	-0.0652	mother < HS degree	-0.0668
	(0.0247)		(0.0262)		(0.0234)
mother >= Coll degree	-0.1675	mother >= Coll degree	-0.1343	mother >= Coll degree	-0.1478
	(0.0255)		(0.0273)		(0.0247)
mother educ missing	0.0582	mother educ missing	0.0427	mother educ missing	0.0415
	(0.0429)		(0.0451)		(0.0404)
father < HS degree	-0.0825	father < HS degree	-0.0877	father < HS degree	-0.0815
	(0.0246)		(0.0261)		(0.0235)
father >= Coll degree	-0.0215	father >= Coll degree	0.0000	father >= Coll degree	-0.0269
	(0.0250)		(0.0271)		(0.0242)
father educ missing	-0.1636	father educ missing	-0.1517	father educ missing	-0.1493
	(0.0270)		(0.0290)		(0.0256)
HH income	3.1006	HH income	2.4538	HH income	2.5928
	(0.4427)		(0.4544)		(0.4312)

HH incomesq	0.0000	HH incomesq	0.0000	HH incomesq	0.0000
	(0.0000)		(0.0000)		(0.0000)
HH income missing	0.1703	HH income missing	0.1719	HH income missing	0.1752
	(0.0248)		(0.0250)		(0.0245)
local UR	0.0020	local UR	0.0015	local UR	0.0013
	(0.0005)		(0.0005)		(0.0004)
teen mother	-0.0864	teen mother	-0.0868	teen mother	-0.0791
	(0.0268)		(0.0281)		(0.0252)
teen mother (missing)	-0.0149	teen mother (missing)	-0.0404	teen mother (missing)	-0.0099
	(0.0369)		(0.0388)		(0.0348)
two parents age 12	-0.0448	two parents age 12	-0.0360	two parents age 12	-0.0496
	(0.0187)		(0.0200)		(0.0179)
two parents age 12 (miss)	-0.0437	two parents age 12 (miss)	-0.0153	two parents age 12 (miss)	-0.0462
	(0.0290)		(0.0301)		(0.0277)
age	-0.1252	age	-0.1253	age	-0.1192
	(0.0076)		(0.0075)		(0.0075)
male	-0.1715	male	-0.1765	male	-0.1363
	(0.0213)		(0.0203)		(0.0200)
black race	0.0553	black race	0.0646	black race	0.0389
	(0.0292)		(0.0278)		(0.0267)
hispanic	0.2526	hispanic	0.2218	hispanic	0.1372
	(0.0306)		(0.0294)		(0.0284)
other race	0.1801	other race	0.1777	other race	0.0896
	(0.0556)		(0.0521)		(0.0526)
foreign	-0.0205	foreign	-0.0371	foreign	-0.0365
	(0.0462)		(0.0436)		(0.0412)
AFQT percentile	-0.0053	AFQT percentile	-0.0041	AFQT percentile	-0.0049
	(0.0005)		(0.0005)		(0.0004)
AFQT missing	0.0525	AFQT missing	0.0413	AFQT missing	0.0034
	(0.0296)		(0.0278)		(0.0268)
married	-0.1239	married	-0.1204	married	-0.1231
	(0.0287)		(0.0286)		(0.0276)
		Four-year College Enrollment Probit			
Constant	0.5978	Constant	0.2298	Constant	0.2140
	(0.2464)		(0.2491)		(0.2410)
labor t-1	-0.0785	labor t-1	-0.0867	labor t-1	-0.0783
	(0.0036)		(0.0035)		(0.0036)

sum(s*l)	0.0864	sum(HS*l)	-0.0124	sumwhite	-0.0012
	(0.0103)		(0.0172)		(0.0111)
years of school	0.5250	sum(2yr*l)	0.2134	sumblue	0.1290
	(0.0081)		(0.0151)		(0.0189)
home cost	0.0004	sum(4yr*l)	0.1033	sumserve	0.1946
	(0.0002)		(0.0164)		(0.0148)
energy costs	0.1951	years of school	0.4933	years of school	0.5382
	(0.0937)		(0.0082)		(0.0079)
dress shirt	-0.0065	home cost	0.0003	home cost	0.0010
	(0.0050)		(0.0002)		(0.0002)
price ground beef	-0.2432	energy costs	0.1827	energy costs	0.1675
	(0.0723)		(0.0935)		(0.0985)
price milk	-0.1504	dress shirt	-0.0062	dress shirt	-0.0110
	(0.0928)		(0.0050)		(0.0049)
mother < HS degree	-0.0109	price ground beef	-0.2329	price ground beef	-0.3416
	(0.0302)		(0.0725)		(0.0719)
mother >= Coll degree	0.3108	price milk	-0.1873	price milk	0.1503
	(0.0242)		(0.0928)		(0.0966)
mother educ missing	0.0730	mother < HS degree	-0.0151	mother < HS degree	-0.0083
	(0.0520)		(0.0296)		(0.0295)
father < HS degree	-0.2024	mother >= Coll degree	0.2888	mother >= Coll degree	0.2995
	(0.0294)		(0.0237)		(0.0236)
father >= Coll degree	0.2603	mother educ missing	0.0701	mother educ missing	0.0711
	(0.0243)		(0.0515)		(0.0510)
father educ missing	0.0085	father < HS degree	-0.1894	father < HS degree	-0.1986
	(0.0317)		(0.0291)		(0.0286)
HH income	-0.5173	father >= Coll degree	0.2509	father >= Coll degree	0.2579
	(0.4412)		(0.0236)		(0.0236)
HH incomesq	0.0000	father educ missing	0.0025	father educ missing	0.0095
	(0.0000)		(0.0315)		(0.0312)
HH income missing	-0.1725	HH income	-0.8034	HH income	0.0030
	(0.0261)		(0.4459)		(0.4355)
local UR	0.0002	HH incomesq	0.0000	HH incomesq	0.0000
	(0.0005)		(0.0000)		(0.0000)
teen mother	-0.1371	HH income missing	-0.1603	HH income missing	-0.1828
	(0.0317)		(0.0263)		(0.0258)

teen mother (missing)	-0.1964	local UR	0.0004	local UR	0.0010
	(0.0409)		(0.0005)		(0.0005)
two parents age 12	0.1896	teen mother	-0.1179	teen mother	-0.1312
	(0.0203)		(0.0308)		(0.0308)
two parents age 12 (miss)	0.1175	teen mother (missing)	-0.1921	teen mother (missing)	-0.2140
	(0.0320)		(0.0399)		(0.0398)
age	-0.1669	two parents age 12	0.1798	two parents age 12	0.1853
	(0.0077)		(0.0198)		(0.0197)
male	-0.1248	two parents age 12 (miss)	0.1124	two parents age 12 (miss)	0.1299
	(0.0233)		(0.0314)		(0.0308)
black race	0.1767	age	-0.1551	age	-0.1719
	(0.0318)		(0.0077)		(0.0076)
hispanic	-0.0289	male	-0.1076	male	-0.1545
	(0.0333)		(0.0220)		(0.0226)
other race	0.1337	black race	0.1419	black race	0.1767
	(0.0559)		(0.0299)		(0.0302)
foreign	0.1661	hispanic	-0.0439	hispanic	0.0845
	(0.0496)		(0.0318)		(0.0325)
AFQT percentile	0.0181	other race	0.1088	other race	0.2345
	(0.0006)		(0.0536)		(0.0533)
AFQT missing	-0.0633	foreign	0.1599	foreign	0.1707
	(0.0318)		(0.0479)		(0.0466)
married	-0.3432	AFQT percentile	0.0185	AFQT percentile	0.0176
	(0.0280)		(0.0005)		(0.0005)
		AFQT missing	-0.0759	AFQT missing	0.0018
			(0.0303)		(0.0298)
		married	-0.3612	married	-0.3642
			(0.0281)		(0.0278)

Graduate School Enrollment Probit

Constant	-5.3654	Constant	-3.7882	Constant	-5.5232
	(0.6818)		(0.7293)		(0.6741)
labor t-1	-0.0001	labor t-1	-0.0017	labor t-1	-0.0013
	(0.0084)		(0.0091)		(0.0084)
sum(s*l)	0.0103	sum(HS*l)	0.0890	sumwhite	0.0303
	(0.0204)		(0.0441)		(0.0234)
		sum(2yr*l)	-0.1390	sumblue	-0.1232
			(0.0678)		(0.0397)

		sum(4yr*l)	-0.0297	sumserve	0.0238
			(0.0287)		(0.0258)
		sum(GS*l)	0.5779		
			(0.0462)		
years of school	0.5518	years of school	0.4337	years of school	0.5542
	(0.0288)		(0.0324)		(0.0293)
home cost	-0.0005	home cost	-0.0005	home cost	-0.0005
	(0.0004)		(0.0004)		(0.0004)
energy costs	0.2891	energy costs	0.1873	energy costs	0.1467
	(0.1974)		(0.2186)		(0.2303)
dress shirt	0.0133	dress shirt	0.0127	dress shirt	0.0144
	(0.0127)		(0.0141)		(0.0129)
price ground beef	0.2590	price ground beef	0.2906	price ground beef	0.2627
	(0.2006)		(0.2024)		(0.1920)
price milk	-0.1672	price milk	-0.2142	price milk	-0.1497
	(0.2173)		(0.2236)		(0.2134)
mother < HS degree	0.0164	mother < HS degree	0.1039	mother < HS degree	0.0135
	(0.1015)		(0.1163)		(0.0981)
mother >= Coll degree	0.2380	mother >= Coll degree	0.2264	mother >= Coll degree	0.2299
	(0.0469)		(0.0537)		(0.0454)
mother educ missing	0.3058	mother educ missing	0.3088	mother educ missing	0.2928
	(0.1183)		(0.1348)		(0.1135)
father < HS degree	0.0400	father < HS degree	-0.0242	father < HS degree	0.0123
	(0.1049)		(0.1204)		(0.1028)
father >= Coll degree	0.0973	father >= Coll degree	0.0774	father >= Coll degree	0.0939
	(0.0469)		(0.0542)		(0.0465)
father educ missing	0.0353	father educ missing	0.0284	father educ missing	0.0218
	(0.0847)		(0.0976)		(0.0828)
HH income	-0.4622	HH income	-0.2479	HH income	-0.7168
	(0.9391)		(1.0065)		(0.9200)
HH incomesq	0.0000	HH incomesq	0.0000	HH incomesq	0.0000
	(0.0000)		(0.0000)		(0.0000)
HH income missing	0.0261	HH income missing	0.0225	HH income missing	0.0300
	(0.0756)		(0.0784)		(0.0748)
local UR	-0.0001	local UR	0.0001	local UR	-0.0007
	(0.0013)		(0.0013)		(0.0013)
teen mother	-0.0452	teen mother	-0.0086	teen mother	-0.0377
	(0.0966)		(0.1181)		(0.0981)

teen mother (missing)	-0.3514	teen mother (missing)	-0.2587	teen mother (missing)	-0.3470
	(0.1563)		(0.1725)		(0.1424)
two parents age 12	-0.2531	two parents age 12	-0.2049	two parents age 12	-0.2504
	(0.0502)		(0.0585)		(0.0482)
two parents age 12 (miss)	0.0155	two parents age 12 (miss)	0.0424	two parents age 12 (miss)	0.0168
	(0.0859)		(0.0996)		(0.0838)
age	-0.0750	age	-0.0886	age	-0.0729
	(0.0204)		(0.0223)		(0.0205)
male	-0.1386	male	-0.1554	male	-0.0841
	(0.0401)		(0.0454)		(0.0407)
black race	0.2941	black race	0.2773	black race	0.2894
	(0.0594)		(0.0687)		(0.0583)
hispanic	0.0967	hispanic	0.1149	hispanic	0.0916
	(0.0708)		(0.0818)		(0.0699)
other race	0.1474	other race	0.0937	other race	0.1195
	(0.0950)		(0.1044)		(0.0928)
foreign	-0.1144	foreign	-0.0550	foreign	-0.1288
	(0.0882)		(0.0997)		(0.0841)
AFQT percentile	0.0075	AFQT percentile	0.0061	AFQT percentile	0.0072
	(0.0011)		(0.0013)		(0.0011)
AFQT missing	0.0870	AFQT missing	0.1039	AFQT missing	0.0673
	(0.0719)		(0.0810)		(0.0722)
married	-0.0002	married	-0.0445	married	0.0136
	(0.0521)		(0.0573)		(0.0510)
High School Employment Ordered Probit				**Blue-collar In-school Work Ordered Probit**	
Constant	-29.9590	Constant	-28.8704	Constant	-19.8123
	(5.3247)		(5.3304)		(8.1617)
labor t-1	-1.3027	labor t-1	-1.2803	labor t-1	-0.1463
	(0.1942)		(0.1965)		(0.1563)
sum(s*l)	16.6341	sum(HS*l)	16.3618	sumwhite	-2.8870
	(0.3736)		(0.3767)		(0.4710)
				sumblue	12.2469
					(0.5728)
				sumserve	-1.5835
					(0.5401)
years of school	4.0594	years of school	4.0199	years of school	0.7680
	(0.2002)		(0.2008)		(0.3143)

home cost	-0.0138	home cost	-0.0134	home cost	0.0188
	(0.0050)		(0.0049)		(0.0062)
energy costs	-0.9772	energy costs	-1.0817	energy costs	-10.1241
	(1.6729)		(1.6736)		(2.9423)
dress shirt	-0.2049	dress shirt	-0.2157	dress shirt	-0.5042
	(0.0530)		(0.0530)		(0.1076)
price ground beef	3.7280	price ground beef	3.4036	price ground beef	-6.4688
	(2.0423)		(2.0468)		(2.1268)
price milk	-3.5618	price milk	-3.6070	price milk	-5.8447
	(1.7291)		(1.7320)		(3.2744)
mother < HS degree	-1.1161	mother < HS degree	-1.0228	mother < HS degree	-0.8894
	(0.3645)		(0.3653)		(0.7460)
mother >= Coll degree	-1.9385	mother >= Coll degree	-2.0152	mother >= Coll degree	-3.5719
	(0.3989)		(0.3992)		(0.6612)
mother educ missing	-2.4478	mother educ missing	-2.4497	mother educ missing	-2.6247
	(0.6772)		(0.6780)		(1.3827)
father < HS degree	-0.4639	father < HS degree	-0.4236	father < HS degree	-0.6976
	(0.3805)		(0.3809)		(0.7466)
father >= Coll degree	-2.1591	father >= Coll degree	-2.2123	father >= Coll degree	-4.0858
	(0.4031)		(0.4039)		(0.6795)
father educ missing	0.3093	father educ missing	0.3488	father educ missing	-1.9592
	(0.4105)		(0.4109)		(0.9126)
HH income	58.3313	HH income	54.3081	HH income	40.8633
	(15.0167)		(15.0628)		(14.6337)
HH incomesq	-0.0002	HH incomesq	-0.0002	HH incomesq	-0.0001
	(0.0001)		(0.0001)		(0.0001)
HH income missing	-0.3479	HH income missing	-0.3376	HH income missing	-1.0601
	(0.4017)		(0.4009)		(0.7172)
local UR	-0.0855	local UR	-0.0838	local UR	-0.0553
	(0.0058)		(0.0058)		(0.0125)
teen mother	0.9987	teen mother	0.9963	teen mother	0.3333
	(0.3984)		(0.3997)		(0.8619)
teen mother (missing)	-0.5551	teen mother (missing)	-0.4444	teen mother (missing)	1.7861
	(0.5568)		(0.5603)		(1.0304)
two parents age 12	-0.6093	two parents age 12	-0.7498	two parents age 12	0.5807
	(0.3007)		(0.3015)		(0.5758)

two parents age 12 (miss)	0.2248	two parents age 12 (miss)	0.1098	two parents age 12 (miss)	1.1723
	(0.4173)		(0.4180)		(0.8457)
				enrolled 2-year coll	0.9540
					(1.1358)
				enrolled 4-year coll	-7.9168
					(1.2893)
				enrolled grad school	-17.8067
					(2.6879)
age	2.3368	age	2.3705	age	1.3913
	(0.1800)		(0.1810)		(0.2734)
male	0.8208	male	0.8395	male	16.5616
	(0.2591)		(0.2609)		(0.6918)
black race	-5.1500	black race	-5.1865	black race	-7.1608
	(0.3528)		(0.3549)		(0.7408)
hispanic	-2.4498	hispanic	-2.4792	hispanic	-3.4178
	(0.3897)		(0.3911)		(0.7701)
other race	-3.4554	other race	-3.5183	other race	-7.1957
	(0.7393)		(0.7390)		(1.5070)
foreign	-1.0954	foreign	-1.0605	foreign	-0.1273
	(0.5202)		(0.5246)		(1.1349)
AFQT percentile	-0.0012	AFQT percentile	0.0005	AFQT percentile	-0.0433
	(0.0058)		(0.0059)		(0.0108)
AFQT missing	-0.9887	AFQT missing	-1.0523	AFQT missing	-0.4061
	(0.3388)		(0.3408)		(0.6533)
married	2.0091	married	2.0331	married	-3.4085
	(2.5223)		(2.5236)		(1.4947)
Variance of Residual	16.4395	Variance of Residual	16.3937	Variance of Residual	23.2075
	(0.1385)		(0.1389)		(0.5737)

Two-year College Employment Ordered Probit				**White-collar In-school Work Ordered Probit**	
Constant	88.2251	Constant	88.2186	Constant	3.0809
	(7.6706)		(7.8776)		(5.2703)
labor t-1	0.7053	labor t-1	0.9379	labor t-1	-0.7062
	(0.1149)		(0.1161)		(0.1079)
sum(s*l)	5.2680	sum(HS*l)	4.2338	sumwhite	9.5608
	(0.3011)		(0.4275)		(0.2899)
		sum(2yr*l)	5.7420	sumblue	-2.4792
			(0.4193)		(0.4582)

		sum(4yr*l)	5.0129	sumserve	-0.5279
			(0.9456)		(0.3523)
years of school	-0.3452	years of school	-0.5819	years of school	3.2235
	(0.3370)		(0.3641)		(0.2261)
home cost	0.0113	home cost	0.0105	home cost	0.0302
	(0.0059)		(0.0060)		(0.0038)
energy costs	-13.2645	energy costs	-13.6468	energy costs	-2.8105
	(2.9533)		(2.9672)		(2.0952)
dress shirt	0.1252	dress shirt	0.1915	dress shirt	-0.2093
	(0.1451)		(0.1464)		(0.0726)
price ground beef	8.8285	price ground beef	8.0864	price ground beef	-12.6886
	(2.0362)		(2.0458)		(1.4625)
price milk	-17.7217	price milk	-17.4062	price milk	-5.7195
	(2.7970)		(2.8438)		(2.2381)
mother < HS degree	1.1925	mother < HS degree	0.9427	mother < HS degree	-1.9238
	(0.7726)		(0.7829)		(0.5315)
mother >= Coll degree	0.0980	mother >= Coll degree	-0.5342	mother >= Coll degree	-1.5595
	(0.7958)		(0.8110)		(0.4796)
mother educ missing	1.2451	mother educ missing	1.5043	mother educ missing	-0.5218
	(1.4116)		(1.3929)		(0.9051)
father < HS degree	1.2803	father < HS degree	1.3848	father < HS degree	1.0294
	(0.7465)		(0.7588)		(0.5360)
father >= Coll degree	-2.2454	father >= Coll degree	-2.2358	father >= Coll degree	-0.5489
	(0.7811)		(0.7937)		(0.4823)
father educ missing	1.0355	father educ missing	0.9329	father educ missing	1.3051
	(0.8473)		(0.8562)		(0.5739)
HH income	19.8981	HH income	25.2293	HH income	16.6065
	(13.8809)		(14.1041)		(10.2427)
HH incomesq	0.0000	HH incomesq	0.0000	HH incomesq	-0.0001
	(0.0001)		(0.0001)		(0.0000)
HH income missing	-2.3498	HH income missing	-2.1924	HH income missing	0.0622
	(0.7312)		(0.7363)		(0.5001)
local UR	-0.1073	local UR	-0.1096	local UR	-0.1035
	(0.0116)		(0.0117)		(0.0081)
teen mother	1.9852	teen mother	2.0274	teen mother	-1.2907
	(0.8192)		(0.8167)		(0.5927)

teen mother (missing)	1.3454	teen mother (missing)	1.5566	teen mother (missing)	-1.3450
	(1.0745)		(1.0802)		(0.7681)
two parents age 12	-0.2666	two parents age 12	-0.3471	two parents age 12	-0.9568
	(0.5780)		(0.5938)		(0.3891)
two parents age 12 (miss)	-0.9885	two parents age 12 (miss)	-1.1867	two parents age 12 (miss)	-1.4381
	(0.8660)		(0.8799)		(0.5964)
age	-1.7919	age	-2.0433	enrolled 2-year coll	11.9769
	(0.2241)		(0.2253)		(0.8465)
male	1.3777	male	1.3533	enrolled 4-year coll	-4.8428
	(0.5209)		(0.5271)		(0.9003)
black race	-1.6614	black race	-1.7055	enrolled grad school	-2.4558
	(0.7234)		(0.7375)		(1.5912)
hispanic	1.5537	hispanic	1.7148	age	0.7742
	(0.7515)		(0.7565)		(0.1882)
other race	-4.9600	other race	-4.8114	male	-5.9039
	(1.3733)		(1.3965)		(0.3659)
foreign	2.8954	foreign	2.7314	black race	0.8201
	(1.0599)		(1.0862)		(0.4959)
AFQT percentile	0.0459	AFQT percentile	0.0240	hispanic	3.0545
	(0.0128)		(0.0134)		(0.5516)
AFQT missing	0.6025	AFQT missing	1.0621	other race	0.2704
	(0.7205)		(0.7275)		(0.9005)
married	-0.4745	married	-0.5098	foreign	1.4317
	(0.9719)		(0.9888)		(0.7203)
				AFQT percentile	0.0784
					(0.0083)
				AFQT missing	-0.4722
					(0.4884)
				married	-0.5445
					(0.8301)
Variance of residual	17.2083	Variance of residual	17.4909	Variance of residual	24.4998
	(0.2294)		(0.2304)		(0.1972)

Four-year College Employment Ordered Probit				**Service In-school Work Ordered Probit**	
Constant	-9.9738	Constant	1.5821	Constant	1.7896
	(7.4495)		(7.6986)		(6.6141)

labor t-1	0.1849	labor t-1	1.7486	labor t-1	-0.1158
	(0.1327)		(0.1429)		(0.1430)
sum(s*l)	5.3690	sum(HS*l)	0.9747	sumwhite	-5.6518
	(0.3103)		(0.4490)		(0.4307)
		sum(2yr*l)	-7.7553	sumblue	-6.9529
			(0.4596)		(0.6640)
		sum(4yr*l)	4.5285	sumserve	13.3559
			(0.4976)		(0.4263)
years of school	-0.0679	years of school	0.7518	years of school	2.4114
	(0.2728)		(0.2851)		(0.2761)
home cost	-0.0491	home cost	-0.0478	home cost	0.0212
	(0.0049)		(0.0047)		(0.0057)
energy costs	2.6561	energy costs	0.4417	energy costs	-9.1530
	(2.5831)		(2.6131)		(2.6451)
dress shirt	0.5671	dress shirt	0.5832	dress shirt	-0.4275
	(0.1361)		(0.1352)		(0.0892)
price ground beef	17.5767	price ground beef	18.5351	price ground beef	-13.3825
	(1.9090)		(1.9224)		(1.8856)
price milk	-3.6842	price milk	-4.1677	price milk	-1.8496
	(2.8281)		(2.8009)		(2.8654)
mother < HS degree	-2.7178	mother < HS degree	-2.4328	mother < HS degree	-0.0435
	(0.8697)		(0.8826)		(0.6475)
mother >= Coll degree	-1.4646	mother >= Coll degree	-2.1423	mother >= Coll degree	-0.1476
	(0.6138)		(0.6341)		(0.5878)
mother educ missing	-3.0833	mother educ missing	-2.5487	mother educ missing	-1.3566
	(1.4100)		(1.4539)		(1.1906)
father < HS degree	-0.8843	father < HS degree	0.3010	father < HS degree	-0.4579
	(0.9112)		(0.9085)		(0.6800)
father >= Coll degree	-1.1164	father >= Coll degree	-1.5288	father >= Coll degree	-0.5174
	(0.6150)		(0.6231)		(0.5862)
father educ missing	2.7980	father educ missing	2.8594	father educ missing	0.4949
	(0.9958)		(0.9997)		(0.7207)
HH income	-26.4201	HH income	-14.9150	HH income	2.2597
	(10.5960)		(10.6750)		(13.0308)
HH incomesq	0.0000	HH incomesq	0.0000	HH incomesq	0.0000
	(0.0000)		(0.0000)		(0.0000)

HH income missing	0.0853	HH income missing	0.2250	HH income missing	1.6311
	(0.7088)		(0.7060)		(0.6258)
local UR	-0.2013	local UR	-0.2047	local UR	-0.0760
	(0.0139)		(0.0136)		(0.0099)
teen mother	-1.7601	teen mother	-1.5772	teen mother	2.5992
	(0.9512)		(1.0171)		(0.6960)
teen mother (missing)	-0.7229	teen mother (missing)	0.2330	teen mother (missing)	-0.4735
	(1.1860)		(1.2184)		(0.9719)
two parents age 12	-0.5407	two parents age 12	-0.8999	two parents age 12	-1.6313
	(0.5898)		(0.6053)		(0.4952)
two parents age 12 (miss)	-1.9750	two parents age 12 (miss)	-2.5143	two parents age 12 (miss)	-0.3390
	(0.9185)		(0.9479)		(0.7366)
				enrolled 2-year coll	-5.6896
					(1.0938)
				enrolled 4-year coll	-6.9184
					(1.1579)
				enrolled grad school	-32.7053
					(2.4024)
age	-0.3685	age	-1.0584	age	0.7589
	(0.2476)		(0.2572)		(0.2307)
male	-1.0009	male	-1.0895	male	-1.0956
	(0.4832)		(0.4914)		(0.4384)
black race	-1.5661	black race	-2.5677	black race	-3.5778
	(0.7096)		(0.7272)		(0.6014)
hispanic	2.3578	hispanic	2.3417	hispanic	-3.1715
	(0.7495)		(0.7624)		(0.6782)
other race	-3.5124	other race	-3.5380	other race	-3.7390
	(1.1590)		(1.1317)		(1.0780)
foreign	3.5051	foreign	4.2170	foreign	-3.8279
	(1.0587)		(1.0434)		(0.9974)
AFQT percentile	0.0413	AFQT percentile	0.0117	AFQT percentile	-0.0339
	(0.0125)		(0.0128)		(0.0098)
AFQT missing	-0.5703	AFQT missing	-0.8239	AFQT missing	-0.7009
	(0.7017)		(0.7271)		(0.6039)
married	-3.5923	married	-3.0695	married	-5.9524
	(0.9564)		(0.9706)		(1.1629)

Variance of residual	21.5189	Variance of residual	21.2749	Variance of residual	27.8736
	(0.2537)		(0.2526)		(0.2983)

Graduate School Employment Ordered Probit

Constant	132.6287	Constant	137.1547
	(25.3332)		(25.6715)
labor t-1	1.0648	labor t-1	0.8629
	(0.3446)		(0.3368)
sum(s*l)	-0.9923	sum(HS*l)	-2.6627
	(0.8453)		(1.6569)
		sum(2yr*l)	10.3018
			(3.0645)
		sum(4yr*l)	-2.6651
			(1.0678)
		sum(GS*l)	2.9460
			(1.5889)
years of school	-1.4006	years of school	-1.6242
	(1.0519)		(1.1331)
home cost	0.0230	home cost	0.0199
	(0.0130)		(0.0141)
energy costs	-14.7282	energy costs	-13.8066
	(7.2256)		(7.7245)
dress shirt	-0.5987	dress shirt	-0.5434
	(0.4934)		(0.4976)
price ground beef	14.3314	price ground beef	15.4999
	(6.9956)		(7.1242)
price milk	-27.6669	price milk	-29.2193
	(7.5346)		(7.4206)
mother < HS degree	-1.0715	mother < HS degree	0.0572
	(4.4650)		(5.0296)
mother >= Coll degree	-2.1719	mother >= Coll degree	-3.0247
	(1.8613)		(1.9336)
mother educ missing	-0.4307	mother educ missing	-1.8724
	(6.7321)		(7.4467)
father < HS degree	-0.9412	father < HS degree	-0.5013
	(4.7720)		(5.6099)

father >= Coll degree	0.0773	father >= Coll degree	0.6514
	(1.9564)		(2.0016)
father educ missing	1.8178	father educ missing	0.9042
	(4.0325)		(4.0697)
HH income	55.1991	HH income	29.5845
	(33.4770)		(34.7950)
HH incomesq	-0.0002	HH incomesq	-0.0001
	(0.0001)		(0.0001)
HH income missing	-2.6676	HH income missing	-1.9752
	(2.5029)		(2.4597)
local UR	-0.2786	local UR	-0.2885
	(0.0482)		(0.0499)
teen mother	-10.6162	teen mother	-10.5302
	(5.5649)		(6.0903)
teen mother (missing)	-5.1622	teen mother (missing)	-5.3155
	(7.0079)		(6.6016)
two parents age 12	-6.5015	two parents age 12	-5.5307
	(1.8239)		(2.0045)
two parents age 12 (miss)	-1.2211	two parents age 12 (miss)	0.3347
	(3.1679)		(3.3970)
age	-1.0375	age	-1.3877
	(0.8575)		(0.8497)
male	0.8783	male	1.7896
	(1.5830)		(1.7420)
black race	0.9755	black race	0.5473
	(1.9975)		(2.1687)
hispanic	0.7239	hispanic	-1.0879
	(3.1098)		(3.3322)
other race	1.0232	other race	1.2925
	(3.2947)		(3.7052)
foreign	-8.3304	foreign	-7.5557
	(3.8055)		(3.9594)
AFQT percentile	-0.1233	AFQT percentile	-0.0888
	(0.0475)		(0.0520)
AFQT missing	-6.1969	AFQT missing	-5.1812
	(2.9861)		(3.3322)

married	1.3949	married	1.0728		
	(1.9780)		(2.0782)		
Variance of residual	18.9933	Variance of residual	18.2369		
	(0.7271)		(0.7399)		
		Non-student Employment Probit			
Constant	3.3633	Constant	3.2209	Constant	3.2783
	(0.2048)		(0.2060)		(0.2054)
labor t-1	0.1226	labor t-1	0.1185	labor t-1	0.1222
	(0.0032)		(0.0033)		(0.0033)
labor t-1sq	-0.0103	labor t-1sq	-0.0097	labor t-1sq	-0.0101
	(0.0007)		(0.0007)		(0.0007)
sum(s*l)	0.0190	sum(HS*l)	0.0164	sumwhite	-0.0176
	(0.0090)		(0.0115)		(0.0126)
		sum(2yr*l)	0.0719	sumblue	0.0338
			(0.0182)		(0.0175)
		sum(4yr*l)	-0.0847	sumserve	0.0629
			(0.0220)		(0.0145)
		sum(GS*l)	-0.0808		
			(0.1375)		
years of school	0.1101	years of school	0.1142	years of school	0.1133
	(0.0048)		(0.0050)		(0.0048)
home cost	0.0008	home cost	0.0008	home cost	0.0008
	(0.0002)		(0.0002)		(0.0002)
energy costs	-0.1873	energy costs	-0.1741	energy costs	-0.2279
	(0.0852)		(0.0855)		(0.0924)
dress shirt	-0.0244	dress shirt	-0.0245	dress shirt	-0.0247
	(0.0041)		(0.0041)		(0.0042)
price ground beef	-0.1434	price ground beef	-0.1466	price ground beef	-0.1522
	(0.0604)		(0.0604)		(0.0606)
price milk	0.0318	price milk	0.0345	price milk	0.0544
	(0.0769)		(0.0772)		(0.0812)
mother < HS degree	0.0139	mother < HS degree	0.0178	mother < HS degree	0.0147
	(0.0176)		(0.0176)		(0.0177)
mother >= Coll degree	0.0503	mother >= Coll degree	0.0516	mother >= Coll degree	0.0483
	(0.0277)		(0.0276)		(0.0276)

mother educ missing	-0.0331	mother educ missing	-0.0289	mother educ missing	-0.0303
	(0.0304)		(0.0305)		(0.0304)
father < HS degree	0.0030	father < HS degree	0.0048	father < HS degree	0.0036
	(0.0186)		(0.0186)		(0.0186)
father >= Coll degree	-0.0947	father >= Coll degree	-0.0891	father >= Coll degree	-0.0947
	(0.0268)		(0.0268)		(0.0267)
father educ missing	-0.0458	father educ missing	-0.0446	father educ missing	-0.0456
	(0.0193)		(0.0193)		(0.0193)
HH income	3.0702	HH income	2.9428	HH income	3.1177
	(0.4158)		(0.4175)		(0.4182)
HH incomesq	0.0000	HH incomesq	0.0000	HH incomesq	0.0000
	(0.0000)		(0.0000)		(0.0000)
HH income missing	-0.2178	HH income missing	-0.2158	HH income missing	-0.2195
	(0.0200)		(0.0200)		(0.0200)
local UR	-0.0029	local UR	-0.0029	local UR	-0.0029
	(0.0004)		(0.0004)		(0.0004)
teen mother	0.0069	teen mother	0.0058	teen mother	0.0031
	(0.0194)		(0.0194)		(0.0194)
teen mother (missing)	-0.0319	teen mother (missing)	-0.0311	teen mother (missing)	-0.0320
	(0.0268)		(0.0268)		(0.0266)
two parents age 12	0.0185	two parents age 12	0.0169	two parents age 12	0.0191
	(0.0162)		(0.0163)		(0.0163)
two parents age 12 (miss)	0.0245	two parents age 12 (miss)	0.0233	two parents age 12 (miss)	0.0227
	(0.0226)		(0.0226)		(0.0226)
age	-0.0882	age	-0.0853	age	-0.0882
	(0.0051)		(0.0051)		(0.0051)
male	0.0073	male	0.0073	male	-0.0010
	(0.0149)		(0.0150)		(0.0151)
black race	-0.1459	black race	-0.1512	black race	-0.1401
	(0.0189)		(0.0191)		(0.0190)
hispanic	0.0335	hispanic	0.0264	hispanic	0.0540
	(0.0222)		(0.0222)		(0.0225)
other race	-0.1052	other race	-0.1072	other race	-0.0907
	(0.0457)		(0.0461)		(0.0456)
foreign	-0.0365	foreign	-0.0338	foreign	-0.0329
	(0.0318)		(0.0315)		(0.0315)
AFQT percentile	0.0017	AFQT percentile	0.0020	AFQT percentile	0.0016
	(0.0004)		(0.0004)		(0.0004)

AFQT missing	-0.0785	AFQT missing	-0.0826	AFQT missing	-0.0716
	(0.0188)		(0.0188)		(0.0187)
married	-0.2085	married	-0.2102	married	-0.2082
	(0.0199)		(0.0199)		(0.0199)

Non-student Hours of Work Ordered Probit

Constant	2.8730	Constant	2.7375	Constant	2.8276
	(0.1030)		(0.1037)		(0.1031)
labor t-1	0.0740	labor t-1	0.0705	labor t-1	0.0741
	(0.0018)		(0.0019)		(0.0018)
labor t-1sq	-0.0035	labor t-1sq	-0.0030	labor t-1sq	-0.0035
	(0.0004)		(0.0004)		(0.0004)
sum(s*l)	0.0148	sum(HS*l)	0.0089	sumwhite	-0.0075
	(0.0038)		(0.0056)		(0.0047)
		sum(2yr*l)	0.0647	sumblue	0.0420
			(0.0067)		(0.0074)
		sum(4yr*l)	-0.0459	sumserve	0.0305
			(0.0074)		(0.0057)
		sum(GS*l)	-0.0144		
			(0.0326)		
years of school	0.0319	years of school	0.0354	years of school	0.0341
	(0.0026)		(0.0027)		(0.0026)
home cost	0.0004	home cost	0.0003	home cost	0.0004
	(0.0001)		(0.0001)		(0.0001)
energy costs	-0.2337	energy costs	-0.2203	energy costs	-0.1339
	(0.0385)		(0.0385)		(0.0427)
dress shirt	-0.0151	dress shirt	-0.0154	dress shirt	-0.0141
	(0.0022)		(0.0022)		(0.0022)
price ground beef	0.1824	price ground beef	0.1726	price ground beef	0.1891
	(0.0281)		(0.0282)		(0.0282)
price milk	-0.2444	price milk	-0.2389	price milk	-0.2726
	(0.0368)		(0.0370)		(0.0382)
mother < HS degree	-0.0036	mother < HS degree	-0.0008	mother < HS degree	-0.0041
	(0.0096)		(0.0095)		(0.0096)
mother >= Coll degree	-0.0382	mother >= Coll degree	-0.0364	mother >= Coll degree	-0.0392
	(0.0123)		(0.0122)		(0.0122)
mother educ missing	0.0245	mother educ missing	0.0266	mother educ missing	0.0226
	(0.0182)		(0.0180)		(0.0183)

father < HS degree	-0.0191	father < HS degree	-0.0185	father < HS degree	-0.0185
	(0.0099)		(0.0098)		(0.0100)
father >= Coll degree	-0.0352	father >= Coll degree	-0.0327	father >= Coll degree	-0.0323
	(0.0125)		(0.0124)		(0.0124)
father educ missing	-0.0054	father educ missing	-0.0045	father educ missing	-0.0057
	(0.0109)		(0.0108)		(0.0109)
HH income	1.2892	HH income	1.1662	HH income	1.3403
	(0.1973)		(0.1969)		(0.1973)
HH incomesq	0.0000	HH incomesq	0.0000	HH incomesq	0.0000
	(0.0000)		(0.0000)		(0.0000)
HH income missing	-0.0674	HH income missing	-0.0665	HH income missing	-0.0674
	(0.0104)		(0.0104)		(0.0104)
local UR	-0.0020	local UR	-0.0020	local UR	-0.0019
	(0.0002)		(0.0002)		(0.0002)
teen mother	0.0076	teen mother	0.0067	teen mother	0.0077
	(0.0105)		(0.0104)		(0.0106)
teen mother (missing)	-0.0242	teen mother (missing)	-0.0256	teen mother (missing)	-0.0244
	(0.0152)		(0.0151)		(0.0152)
two parents age 12	0.0346	two parents age 12	0.0335	two parents age 12	0.0322
	(0.0084)		(0.0083)		(0.0083)
two parents age 12 (miss)	0.0253	two parents age 12 (miss)	0.0251	two parents age 12 (miss)	0.0255
	(0.0122)		(0.0120)		(0.0121)
age	-0.0484	age	-0.0450	age	-0.0480
	(0.0028)		(0.0028)		(0.0028)
male	0.1775	male	0.1787	male	0.1665
	(0.0078)		(0.0077)		(0.0080)
black race	-0.0605	black race	-0.0640	black race	-0.0641
	(0.0103)		(0.0102)		(0.0103)
hispanic	0.0226	hispanic	0.0167	hispanic	0.0231
	(0.0111)		(0.0109)		(0.0115)
other race	-0.0736	other race	-0.0758	other race	-0.0679
	(0.0242)		(0.0237)		(0.0239)
foreign	0.0440	foreign	0.0474	foreign	0.0479
	(0.0172)		(0.0168)		(0.0168)
AFQT percentile	0.0002	AFQT percentile	0.0006	AFQT percentile	0.0003
	(0.0002)		(0.0002)		(0.0002)
AFQT missing	0.0336	AFQT missing	0.0317	AFQT missing	0.0387
	(0.0098)		(0.0097)		(0.0097)

married	-0.0294	married	-0.0311	married	-0.0346
	(0.0093)		(0.0092)		(0.0093)
Variance of residual	0.7194	Variance of residual	0.7188	Variance of residual	0.7193
	(0.0034)		(0.0034)		(0.0034)
		Wage Equation Ordered Probit			
Constant	1.6167	Constant	1.5669	Constant	1.5725
	(0.0485)		(0.0493)		(0.0488)
labor t-1	0.0186	labor t-1	0.0151	labor t-1	0.0182
	(0.0008)		(0.0009)		(0.0009)
labor t-1sq	-0.0014	labor t-1sq	-0.0008	labor t-1sq	-0.0014
	(0.0002)		(0.0002)		(0.0002)
sum(s*l)	0.0054	sum(s*l)	-0.0389	sum(s*l)	-0.0132
	(0.0019)		(0.0035)		(0.0022)
		sum(2yr*l)	0.1399	sumblue	0.0493
			(0.0046)		(0.0038)
		sum(4yr*l)	-0.0266	sumserve	0.0348
			(0.0046)		(0.0033)
		sum(GS*l)	0.0892		
			(0.0152)		
years of school	0.0262	years of school	0.0247	years of school	0.0279
	(0.0013)		(0.0014)		(0.0013)
home cost	0.0010	home cost	0.0009	home cost	0.0008
	(0.0000)		(0.0000)		(0.0000)
energy costs	-0.0196	energy costs	-0.0127	energy costs	-0.0671
	(0.0176)		(0.0176)		(0.0196)
dress shirt	-0.0010	dress shirt	-0.0021	dress shirt	-0.0013
	(0.0010)		(0.0010)		(0.0010)
price ground beef	-0.0411	price ground beef	-0.0530	price ground beef	-0.0462
	(0.0130)		(0.0128)		(0.0130)
price milk	0.0212	price milk	0.0187	price milk	0.0080
	(0.0160)		(0.0158)		(0.0163)
local UR	-0.0007	local UR	-0.0007	local UR	-0.0008
	(0.0001)		(0.0001)		(0.0001)
age	0.0116	age	0.0144	age	0.0123
	(0.0014)		(0.0015)		(0.0014)
male	0.1125	male	0.1169	male	0.1044
	(0.0050)		(0.0051)		(0.0051)

black race	-0.0387	black race	-0.0491	black race	-0.0345
	(0.0066)		(0.0068)		(0.0067)
hispanic	0.0107	hispanic	-0.0030	hispanic	0.0175
	(0.0069)		(0.0070)		(0.0071)
other race	0.0500	other race	0.0434	other race	0.0609
	(0.0136)		(0.0139)		(0.0134)
foreign	0.0203	foreign	0.0239	foreign	0.0210
	(0.0112)		(0.0114)		(0.0110)
AFQT percentile	0.0020	AFQT percentile	0.0025	AFQT percentile	0.0020
	(0.0001)		(0.0001)		(0.0001)
AFQT missing	-0.0365	AFQT missing	-0.0421	AFQT missing	-0.0338
	(0.0066)		(0.0068)		(0.0066)
married	0.0514	married	0.0469	married	0.0522
	(0.0043)		(0.0045)		(0.0043)
Variance of residual	0.2961	Variance of residual	0.2838	Variance of residual	0.2921
	(0.0012)		(0.0012)		(0.0012)

Factor Loadings for Auxilary Equations

HS enrollment	0.4438	HS enrollment	0.4747	HS enrollment	0.3039
	(0.0759)		(0.0635)		(0.0729)
2-year enrollment	-3.2719	2-year enrollment	-2.3427	2-year enrollment	-2.7261
	(0.0761)		(0.0644)		(0.0667)
4-year enrollment	3.8845	4-year enrollment	3.3556	4-year enrollment	3.5876
	(0.0666)		(0.0608)		(0.0642)
grad school enrollment	-0.2160	grad school enrollment	-0.8213	grad school enrollment	-0.1519
	(0.1432)		(0.1577)		(0.1443)
HS employment	1.2356	HS employment	5.4939	in-school blue-collar	-1.6553
	(0.8465)		(0.7022)		(1.7698)
2-year employment	23.2941	2-year employment	5.3566	in-school white-collar	32.1292
	(2.2841)		(1.9369)		(1.1490)
4-year employment	17.9270	4-year employment	10.4851	in-school service	-25.0064
	(1.6306)		(1.6052)		(1.5266)
grad school employment	44.9946	grad school employment	47.3754	no school employment	0.8216
	(5.2988)		(5.1274)		(0.0520)
no school employment	0.8766	no school employment	0.8140	no school hours of work	0.7119
	(0.0541)		(0.0455)		(0.0245)

no school hours of work	0.7269	no school hours of work	0.6704		
	(0.0248)		(0.0217)		
Points of Support					
Point1 (Fixed)	-0.5631	Point1 (Fixed)	-0.5631	Point1 (Fixed)	-0.5631
Point2	-0.3443	Point2	-0.2851	Point2	-0.3215
	(0.0070)		(0.0070)		(0.0071)
Point3	-0.1321	Point3	-0.0373	Point3	-0.0985
	(0.0091)		(0.0088)		(0.0090)
Point4	0.1303	Point4	0.2701	Point4	0.1764
	(0.0113)		(0.0109)		(0.0112)
Estimated Probability Weights for Each Point of Support (CDF Points from Standard Normal Distribution)					
Weight1	-1.2901	Weight1	-1.2996	Weight1	-1.3546
	(0.0500)		(0.0367)		(0.0451)
Weight2	0.0265	Weight2	-0.0127	Weight2	-0.0486
	(0.0352)		(0.0274)		(0.0321)
Weight3	1.1621	Weight3	1.0846	Weight3	1.1661
	(0.0371)		(0.0286)		(0.0333)